DETERMINANTS OF THE SLOPE OF S&P 500 INDEX OPTIONS: A JOINT ANALYSIS OF MACROECONOMIC ANNOUNCEMENTS AND PRIVATE INFORMATION

A Ph.D. Dissertation

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September 2014

To my Family

DETERMINANTS OF THE SLOPE OF S&P 500 INDEX OPTIONS: A JOINT ANALYSIS OF MACROECONOMIC ANNOUNCEMENTS AND PRIVATE INFORMATION

Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

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DOCTOR OF PHILOSOPHY

in

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MANAGEMENT
İHSAN DOĞRAMACI BİLKENT UNIVERSITY
ANKARA

September 2014

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Management.

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ABSTRACT

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September 2014

This thesis analyzes the possible determinants of the observed implied volatility skew of S&P 500 index options. The thesis will also examine the high frequency changes in VIX in response to macroeconomic announcements. Finally the effect of presidential announcements on stock market volatility will be investigated.

Keywords: Implied volatility skew, VIX, volatility, private information, macroeconomic announcements, presidential announcements

ÖZET

S&P 500 ENDEKS OPSİYONLARINDAN ELDE EDİLEN ZIMNİ OYNAKLIK EĞRİSİNİN BELİRLEYİCİ FAKTÖRLERİ: MAKROEKONOMİK DUYURULARIN VE ÖZEL BİLGİNİN (VPIN) BİRLİKTE ANALİZİ

Yaşar, Burze

Doktora, İşletme Bölümü

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Eylül 2014

Bu tez, S&P 500 Endeks opsiyonlarından elde edilen zımni oynaklık eğrisinin çarpıklığının belirleyici faktörlerini analiz etmiştir. Bu çalışma ayrıca VIX Oynaklık Endeksinin makroekonomik duyurular ile ilişkisini yüksek frekansta incelemiştir. Son olarak da başkanların duyurularının hisse senedi piyasası oynaklığına etkilerini araştırmıştır.

Anahtar Kelimeler: Oynaklık çarpıklığı, VIX, oynaklık, özel bilgi, makroekonomik duyurular, başkanların duyuruları

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TABLE OF CONTENTS

ABSTRACT…………………………………………………………………… iii

ÖZET………………………………………………………………………... …iv

ACKNOWLEDGEMENTS.. ……………………………………………………......v

TABLE OF CONTENTS……………………………………………………… …vi

CHAPTER I: INTRODUCTION.. 1

CHAPTER II: DETERMINANTS OF IMPLIED VOLATILITY SLOPE OF SPX OPTIONS.. 6

2.1 Literature Review.. 9

2.2 Data and Variable Construction.. 14

2.2.1 Data.. 14

2.2.2 Variable Construction.. 17

2.2.2.1 Slope.. 17

2.2.2.2 Liquidity and Transaction Costs.. 20

2.2.2.3 Momentum.. 22

2.2.2.4 Time to Maturity and Market Uncertainty.. 23

2.2.2.5 Net Buying Pressure.. 23

2.2.2.6 Volume-Synchronized Probability of Informed Trading 26

2.3 Empirical Results.. 28

2.4 Conclusion.. 38

CHAPTER III: IMPACT OF MACROECONOMIC ANNOUNCEMENTS ON IMPLIED VOLATILITY SLOPE OF SPX OPTIONS AND VIX 41

3.1 Data Filtering and Analysis.. 43

3.1.1 Momentum and Liquidity Effects.. 48

3.2 Empirical Results.. 49

3.2.1 Asymmetric News Effects.. 51

3.2.2 VIX and Macroeconomic Announcements 55
3.3 Conclusion 57
CHAPTER IV: PRESIDENTIAL RHETORIC AND
STOCK MARKET VOLATILITY 58
4.1 Introduction 58
4.2 Testable Hypotheses 64
4.3 Methodology 66
4.3.1 Data 66
4.3.1.1 Presidential Signals Data 67
4.3.1.2 Stock Market Data 68
4.3.2 Presidential Signal Categorization and
Inter-rater Reliability 69
4.3.3 Presidential Signal Categories 74
4.3.4 Controlling for Macroeconomic Announcements 81
4.4 Empirical Tests 83
4.5 Post-hoc Analysis 87
4.6 Conclusion 89
CHAPTER V: CONCLUSION 92
BIBLIOGRAPHY 93

CHAPTER I

INTRODUCTION

This thesis examines the high frequency characteristics of S&P 500 index options' implied volatility skew and VIX. Slope of implied volatility skew is a good proxy for jump risk and investor risk aversion. VIX is a good measure of both market risk and investor 'fear gauge'. In an attempt to explain changes in these parameters proxied by slope and VIX, this study explores a broad range possible determinants and macroeconomic announcements. The last chapter covers another aspect of marketplace information and explores whether presidential rhetoric affects financial market volatility.

The volatility smirk refers to the fact that for the same underlying asset, the implied volatilities of options with low strike prices are higher than options with high strike prices. This is contrary to well-known Black-Scholes (1973) option pricing model which predicts that the implied volatility shall be constant for every option which have the same maturity and are written on the same underlying asset. Volatility smirk in the options prices is one of the puzzling anomalies that are yet to be solved in the finance literature. Literature suggests that the implied volatility smirk is related to investor risk aversion to negative jumps and crashes in the prices (Bates 1991; Pan 2002). Recent literature supports that steepness of implied volatility skew is related to jump risk and investors require risk premiums for perceived crash risk (Bollerslev and Todorov, 2011; Yan, 2011; Conrad, Dittmar and Ghysels, 2013).

Since the documentation of the implied volatility skew by MacBeth and Merville (1979) and Rubinstein (1985), academicians investigate the possible reasons for the skew and the option pricing implications. These models relax the constant volatility assumption of the Black-Scholes model and incorporate stochastic volatility, jumps or deterministic volatility in their option pricing models (Heston, 1993; Bates, 1996). Bakshi, Cao and Chen (1997) compare different option pricing models and find that stochastic volatility models with jumps outperform other models and explain the empirical observed volatility skew pattern or anomaly much better.

The second line of researchers uses demand based arguments for option pricing and suggests that market participants' supply and demand for options is an important determinant in the pattern of implied volatilities. The argument is based on limits to arbitrage theorem: Market makers cannot afford to sell an infinite number of contracts for a specific option series. When demand for a specific series is high, market makers' portfolios become unbalanced and risky and they have to charge higher option prices. In this respect, excess demand (supply) for particular option series will cause implied volatility to increase (decrease). Bollen and Whaley (2004) show that net buying pressure for each option moneyness category significantly affects the shape of implied volatility function for S&P 500 index options. Gârleanu, Pedersen, and Poteshman's (2009) demand-based option model confirms prior results. They find that ATM options which have more than average implied volatility also have more than average demand. However, they do not provide evidence on origins of the buying pressure.

Other papers take a different perspective and investigate possible determinants of implied volatility smile through cross-sectional analysis. In this literature, the purpose is to understand the dynamics and determinants of the volatility skew rather than developing a new option pricing model. Researchers examine whether various firm characteristics are related to implied volatility smirk. For example, Toft and Prucyk (1997) explain implied volatility skews by leverage and debt covenants for individual equity options. They find that the higher the firm leverage, the more pronounced the implied volatility skews. Moreover, the options on the firms that have stricter debt covenants also exhibit more pronounced volatility skews. Van Buskirk (2011) confirms their results. He also finds a negative relation between the market-to-book ratio and implied volatility skew. Dennis and Mayhew (2002) investigate whether variables such as leverage, firm size, beta, trading volume, and/or the put/call volume ratio explain cross-sectional variations in risk neutral skewness measure of Bakshi, Kapadia, and Madan (2003). Risk neutral skewness and kurtosis are closely related to the level and slope of implied volatility curve (Bakshi et al., 2003). Contrary to what Toft and Prucyk (1997) find, Dennis and Mayhew (2002) find the higher the leverage the less pronounced the volatility skews. As seen from the above discussion the evidence related to the determinants of volatility skew is mixed.

The motivation of this thesis is to provide a better frame for the determinants of volatility skew of S&P 500 options in a high frequency setting. A clearer comprehension about the factors that affect the slope is important for developing new option pricing models and devising proper hedging and investment strategies. In the first chapter, besides variables that have been shown to affect slope of implied volatility skew such as transaction costs and market uncertainty, we also investigate the effect of private information using a new metric, Volume Synchronized Probability of Informed Trading (VPIN) developed by Easley et al. (2012). This metric aims to measure order flow toxicity or adverse selection risk encountered by market makers in high frequency environments. We then investigate whether the relation between the implied volatility skews and VPIN is reinforced at macroeconomic announcement times. Macroeconomic announcements provide an avenue for investors to trade more aggressively on their private information (Pasquariello and Vega, 2007).

The second chapter analyzes the effect of 23 macro announcements, grouped under categories of inflation, investment, employment, real activity and forward-looking, on 2006 high-frequency behavior of VIX and slope of S&P 500 index options. Literature accepts VIX as a good proxy for future index volatility. We aim to analyze the changes of VIX in response to macroeconomic announcements. We first analyze the effects of macroeconomic announcements on the first difference of VIX and slope and then investigate whether there is asymmetric news impact. We also analyze the effect of surprises contained in the announcements by computing the difference between the announced and expected figures.

In the final chapter we investigate whether financial market volatility is influenced by presidential rhetoric. We explore this hypothesis by studying over 51,000 pages of presidential announcements over nearly 20 years of presidential signals about the deficit, economy and inflation/interest rates. Presidential rhetoric is an important research area as presidents are continuously making announcements and research suggests that news from a reliable source will lead to more portfolio rebalancing. Illeditsch (2011) argues that when investors receive information that is difficult to process, investors' desire to hedge ambiguity leads to excess volatility. We argue that presidential rhetoric is an important and reliable source of information and affects market place volatility with negative and positive presidential signals leading to higher volatility.

All of the chapters serve to our understanding of volatility and slope of implied volatility skew and this is a crucial aspect of risk management. In this respect, this thesis aims to contribute to developing pricing models and hedging strategies. Our results justify why traders shall closely monitor slope to understand how jump risk and risk aversion are evolving during a trading day.

CHAPTER II

DETERMINANTS OF IMPLIED VOLATILITY SLOPE OF S&P 500 OPTIONS

Implied volatility skew refers to the pattern where implied volatilities of at-the-money (ATM) options are lower than out-of-the-money (OTM) options. This empirical observation is an anomaly since the Black-Scholes Option Pricing Model presumes that for the same underlying asset, the implied volatilities shall be constant in the same maturity category across different strike prices. Recent research uses slope of implied volatility skew as a good proxy of ex-ante crash risk (Santa Clara and Yan 2010, Yan 2011). This paper examines the link between this important proxy and several market microstructure variables using high-frequency data for S&P 500 index options. We find that order flow toxicity measure of Easley, de Prado and O'Hara (2012) is one of the important determinants of the slope of the volatility skew besides transactions costs, market uncertainty and net buying pressure. Understanding the factors affecting implied volatility skew is important for the option pricing literature. The findings of this study are beneficial to option traders and financial analysts who closely monitor the volatility skew as they believe that it carries important information regarding the market structure and the risk aversion of market participants.

Alternative option pricing models attempt to account for the volatility skews by relaxing the distributional assumptions of the Black-Scholes model. However, none of the models provides a satisfactory explanation for this empirical irregularity. Given the limited success of these models, some researchers try to explain the economic determinants of the implied volatility function. Pena, Rubio and Serna (1999) is the first paper in that strain of literature and argue that transaction costs are the main determinants of the slope of the volatility skew of the Spanish Index Options. They also document that time to expiration and uncertainty of the market are important factors. Dumas, Fleming and Whaley (1998) suggest that past changes in the index level and volatility surface may be related. Other researchers propose demand and supply based explanations to the volatility skews. For example, Bollen and Whaley (2004) suggest that the implied volatility skew of index options could be attributed to high demand from institutional investors for puts as portfolio insurance. Han (2008) takes a behavioral approach and relate implied volatility smile to investor sentiment. Liquidity is also reported as a factor that might affect the steepness of the implied volatility skew with mixed findings for different options.

The motivation of this study is to provide a better frame for the determinants of volatility skew of S&P 500 options in a high frequency setting. Besides variables that have shown to affect slope of implied volatility skew such as transaction costs and market uncertainty, we also investigate the effect of private information using a new metric, Volume Synchronized Probability of Informed Trading (VPIN) developed by Easley et al. (2012). This metric aims to measure order flow toxicity or adverse selection risk encountered by market makers in high frequency environments. VPIN is based on order imbalance and trade intensity in the market as informed traders are expected to trade on one side of the market and cause unbalanced volume. If market makers sense that order flow is toxic then they either cease or reduce their market making activities. In case they choose to continue to provide liquidity to the market, they charge higher prices for increased risk. Therefore we hypothesize that higher variability in slope of implied volatility skew will be observed with changes in VPIN level. We find that VPIN is a statistically significant factor that affects the shape of the volatility skews even after controlling for net buying pressure of Bollen and Whaley and other variables.

We then investigate the relation between the implied volatility skews and VPIN at macroeconomic announcement times. Macroeconomic announcements provide an avenue for investors to trade more aggressively on their private information (Pasquariello and Vega, 2007). In an earlier study, Admati and Pfleiderer (1988) document that informed traders try to time their trades at times of high level of trading and liquidity. 23 macro announcements are analyzed for 2006. We also analyze the surprises contained in these announcements by computing the difference between the announced and expected figures. We find that uncertainty resolution affects slope at the time of macroeconomic announcements and when the surprise component is high.

Our contribution can be summarized as follows. First, this paper analyzes possible determinants of slope of S&P 500 options in a high-frequency setting. Second, it uses a new proxy for the level of informed trading and order flow toxicity (VPIN) and shows that adverse selection risk significantly affects the shape of the volatility skews besides market uncertainty, transaction costs and net buying pressure. Finally, the analysis differs from standard time based approaches and documents high-frequency behavior of slope with respect to volume.

The remainder of the paper is organized as follows. Section one discusses related literature. Section two describes the data and variable construction. Section three presents the results of the analysis of the determinants of implied volatility skews. Section four concludes the paper.

2.1 Literature Review

The Black-Scholes Option Pricing Model presumes that for the same underlying asset, the implied volatilities shall be constant in the same maturity category across different strike prices. MacBeth and Merville (1979) and Rubinstein (1985) are the first papers to document that options on the same underlying with the same maturity dates have different implied volatilities across different strike prices. This anomaly is known as the volatility skew and takes the shape of a smile or a smirk depending on the instrument. Academicians investigate the possible reasons for this anomaly and the option pricing implications. Hull (1993) suggests that the empirical violations of the assumption of the normality of the log returns may cause this anomaly. One strand of literature has relaxed the distribution assumption of the Black-Scholes model (Heston, 1993; Bates, 1996), and incorporated stochastic volatility and jumps in option pricing models.

Other researchers use demand based arguments for option pricing and suggest that market participants' supply and demand for options is an important determinant in the pattern of implied volatilities. The argument is based on limits to arbitrage theorem: Market makers cannot afford to sell an infinite number of contracts for a specific option series. When demand for a specific series is high, market makers' portfolios become unbalanced and risky and they have to charge higher option prices. In this respect, excess demand (supply) for particular option series will cause implied volatility to increase (decrease). Bollen and Whaley (2004) show that net buying pressure for each option moneyness category significantly affects the shape of implied volatility function for S&P 500 index options[1]. Gârleanu, Pedersen, and Poteshman's

[1] Bollen and Whaley (2004) note that there is considerable difference between trading volume and net buying pressure and these two are not necessarily highly correlated. For example trading volume may be high on days with significant information flow, but net buying pressure can be essentially zero if there are as many public orders to buy as to sell. They suggest the underlying reason why Dennis and Mayhew (2002) could not find any relation between risk neutral skewness and the ratio of average daily put volume to average daily call volume as a measure for public order is because trading volume is not a precise measure for net buying pressure. Moreover aggregate option volumes do not take into consideration option moneyness and both deep out-of-the-money and deep in-the-money puts are treated the same way.

(2009) demand-based option model confirms prior results. They find that ATM options which have more than average implied volatility also have more than average demand.

Other papers take a different perspective and investigate possible determinants of implied volatility smile through cross-sectional analysis. In this literature, the purpose is to understand the dynamics and determinants of the volatility skew rather than to develop a new option pricing model. For example, Toft and Prucyk (1997) explain implied volatility skews by leverage and debt covenants for individual equity options. They find that the higher the firm leverage, the more pronounced the implied volatility skews. Moreover, the options on the firms that have stricter debt covenants also exhibit more pronounced volatility skews. Dennis and Mayhew (2002) investigate whether variables such as leverage, firm size, beta, trading volume, and/or the put/call volume ratio explain cross-sectional variations in risk neutral skewness measure of Bakshi, Kapadia, and Madan (2003). Risk neutral skewness and kurtosis are closely related to the level and slope of implied volatility curve (Bakshi et al., 2003). Contrary to what Toft and Prucyk (1997) find, Dennis and Mayhew (2002) find the higher the leverage the less pronounced the volatility skews. They also document that larger firms with greater betas have more negative skews and firms with higher trading volume have more positive skews. Duan and Wei (2009) extend their study and argue that systematic risk is the driver for the observed pattern in implied volatility curve. After controlling for the overall level of total risk they find that for individual equity options, a steeper implied volatility curve is associated with a higher amount of systematic risk. From an accounting perspective, Kim and Zhang (2010) show that steepness of option-implied volatility smirks in individual equity options is significantly and positively related to financial reporting opacity. As seen from the above discussion, the evidence related to the determinants of volatility skew is mixed.

One line of literature suggests heterogeneous beliefs and investor sentiment to be a determining factor for the option implied volatility smile. One example is Buraschi and Jiltsov (2006) who develop an option pricing model where agents have heterogeneous beliefs on expected dividends. Han (2008) links implied volatility smile to investor sentiment. Liquidity is yet another factor that seems to affect the steepness of the implied volatility curve. Chou, Chung, and Hsiao (2009) report that the more liquid the option market, the steeper the volatility skews. Nordén and Xu (2012) find that options in different moneyness categories have significant differences in liquidity and an improvement in the liquidity of an OTM put option relative to a concurrent ATM call option is found to lead to lower steepness. Deuskar, Gupta, and Subrahmanyam (2008) find a significant link between liquidity effect and the shape of the volatility skews only for long maturity options written on interest rates.

This study also contributes to the literature that investigates the determinants of jump risk. Yan (2011) argues that slope, defined as the difference between implied volatility of ATM puts and calls, measures the local steepness of the volatility skews and is a good proxy for jump risk. Understanding jump risk is important as Andersen Bollerslev and Diebold (2003) show that volatility estimates are more accurate when jumps are differentiated. Xing, Zhang, Zhao (2010) suggest that volatility skews contains information related to jumps in at least three aspects: 1) the probability of a negative price jump 2) the expected size of the price jump 3) the jump risk premium that also compensates investors for the expected size of the jump. Cremers, Driessen, Maenhout, and Weinbaum (2008) show that volatility skews is a significant determinant of corporate credit spreads which are also highly sensitive to jump risk. Therefore, our study will also shed light on the possible determinants of the jumps in option prices.

This paper is also related to the literature that investigates the effects of macroeconomic news on financial markets. Ederington and Lee (1996) are the first to study the impact of news on option implied volatility. Kearney and Lombra (2004) find a significant positive relation between the CBOE volatility index, VIX, and unanticipated changes in employment, but not inflation. Andersen, Bollerslev, Diebold and Vega (2007), investigate the impact of public news on returns and volatility in three markets: foreign exchange, bond and equity markets using high-frequency intraday data. They find that macro announcement surprises significantly affect the returns and volatilities in all three markets. Onan, Salih and Yasar (2014) associate high-frequency changes in VIX and slope with macroeconomic announcements. Different from other studies, this paper looks at the impact of VPIN and other potential factors on slope at macroeconomic announcement times.

2.2 Data and Variable Construction

The purpose of this section is to describe the data, volume time approach and the variables that we use as possible determinants of slope of implied volatility skew of S&P 500 Index Options.

2.2.1 Data

The data consists of tick-by-tick data of S&P 500 Index (SPX) option contracts and is obtained from Berkeley Options Database for a total of 251 trading days in 2006[2]. The dataset is derived from the Market Data Report (MDR file) of the Chicago Board Options Exchange (CBOE) and includes time-stamped (in seconds) option trades and quotes (options of all strikes and maturities) including expiration date, put – call code, exercise price, bid and ask prices and contemporaneous price of the underlying S&P 500 Index. Daily S&P 500 continuous dividend yields are obtained from the DataStream database.

Tick by tick options data is filtered based on maturity, no-arbitrage lower option boundaries and for obvious reporting errors and outliers. In order to avoid implied volatilities that are likely to be measured with error, only options with bid

[2] Sample data does not coincide with US financial crisis of 2007-2009.

prices greater than zero are used[3]. Put-Call parity violations are not filtered as they might contain evidence related to the trading activity of informed traders (Cremers and Weinbaum, 2010). We include options that have maturities between 15 and 45 trading days since these are the most liquid options. This study does not include options that have maturities shorter than 15 days, as shorter term options have relatively small time premiums and are substantially unreliable when calculating option implied volatilities (Dumas et. al., 1998).

Trading hours on the CBOE begin at 8:30 a.m. (CST) and end at 3:15 p.m. (CST); however, New York Stock Exchange (NYSE) closes at 4:00 p.m. (EST) and this corresponds to 3.00 p.m. (CST). Therefore, we delete all option quotes after 3:00 p.m. (CST) in order not to have non-synchronicity problem in our analysis. We plot the intraday behavior of trading activity in Figure 1. We observe that the average number of contracts traded and dollar volume are highest within the first trading hour. Average number of contracts then gradually decreases till noon and slightly increases towards closing. Average volume makes a peak in the early afternoon between 12:30 to 13:30 and towards closing around 15:00. The observed patterns could be attributed to the macroeconomic announcement timings at 8:30 EST and market opening effects.

One of the problems of working with high frequency data is arrival of market ticks at random time. Regular time-series econometric tools which frequently use

[3] In a same manner, but a bit different approach, some authors use options with bid-ask midpoints higher than 0.125 or 0.25.

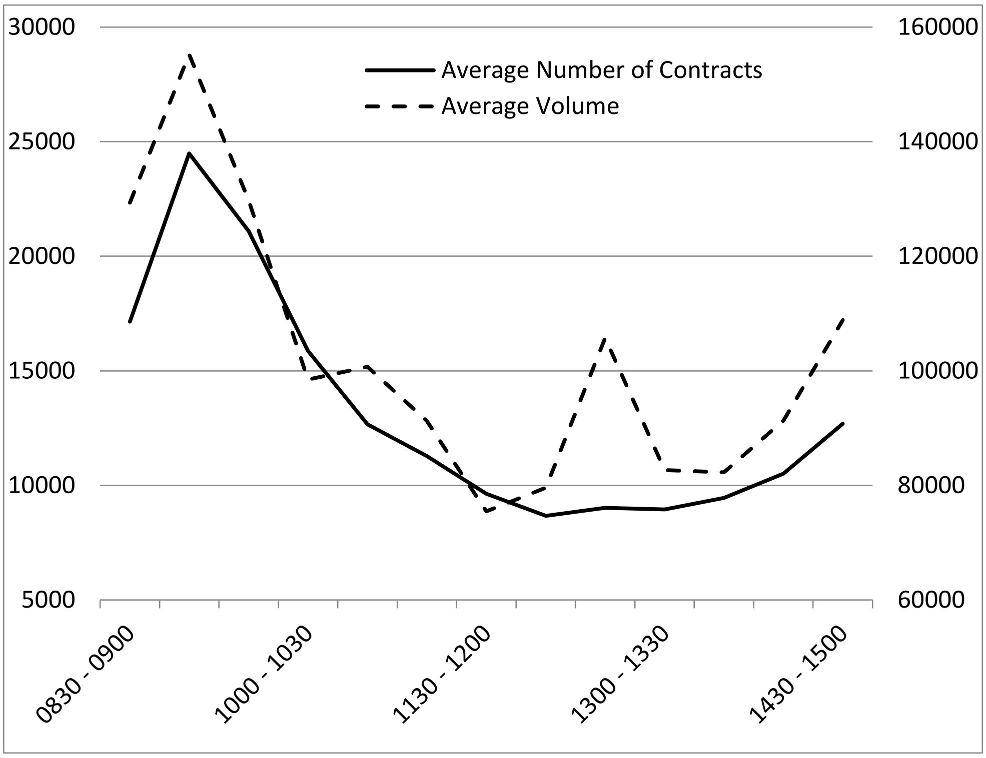

Figure 1: Intraday behavior of S&P 500 trading Figure shows the intraday (thirty-min) behavior of average number of contracts and average dollar volume for SPX thirty-day options for a total observations of 585,991 during 2006.

backward operators cannot be applied to irregularly spaced or nonhomogeneous time series (Gencay et al., 2001). Traditional approach to this problem is to equally space time-series data and work with time bars. Alternative approach to working with nonhomogeneous data is to use volume bars. Every time a predetermined level of volume is traded in the market marks the separation of volume bars. In this study, we employ volume bars for analysis or in other words work in volume time. Easley et al. (2012) argue that in a high frequency framework, volume time, measured by volume increments, is a more relevant metric compared to clock time as trades take place in milliseconds.

Following Easley et al (2012), we group sequential trades in the so-called volume buckets until their combined volume equals constant size, V, which is an exogenously defined fixed size. In the analysis, we define V as one thirteenth of the average daily volume. If the size of the last trade that is needed to complete a bucket is greater than needed, then excess part of that trade is assigned to the next bucket. The time needed to fill a bucket is related to the existence of amount of information. Easley and O'Hara (1992) suggest that the time between trades is correlated with the presence of new information. Therefore if a very relevant piece of news arrives to the market, we may expect to see a lot of activity in the market and volume buckets filling up quickly. Hence, volume time is updated in stochastic time matching the arrival rate of information. Easley et al. (2012) argue that equal volume intervals stand for comparable amount of information.

2.2.2 Variable Construction

2.2.2.1 Slope

We first group options in moneyness categories according to their deltas as in Bollen and Whaley (2004). Besides forward price of the underlying asset, an option's moneyness also depends on volatility of the underlying asset and time to maturity of the option and delta accounts for these two factors. Table I lists the upper and lower

Table I

Moneyness Category Definitions of S&P 500 Index Options

Table presents delta upper and lower bounds of the moneyness categories of S&P 500 Index Options. Options with absolute deltas below 0.02 and above 0.98 are excluded.

Option Category	Call Option Delta Lower Bound	Call Option Delta Upper Bound
DITMC - Deep in the money call option	0,875	0,98
ITMC - In the money call option	0,625	0,875
ATMC - At the money call option	0,375	0,625
OTMC - Out of the money call option	0,125	0,375
DOTMC - Deep out of the money call option	0,02	0,125

Option Category	Put Option Delta Lower Bound	Put Option Delta Upper Bound
DITMP - Deep in the money put option	- 0,98	- 0,875
ITMP - In the money put option	- 0,875	- 0,625
ATMP - At the money put option	- 0,625	- 0,375
OTMP - Out of the money put option	- 0,375	- 0,125
DOTMP - Deep out of the money put option	- 0,125	- 0,02

boundaries of moneyness categories. Options with absolute deltas below 0.02 or above 0.98 are excluded to avoid price distortions.

We calculate implied volatilities of the European-style S&P 500 index options for each moneyness category using the extension of Black and Scholes (1973) option pricing formula that incorporates continuous dividends. To proxy risk-free rate, we calculate implied risk-free rate from put-call parity relations of options written on

S&P 500 Index. Daily SPX dividend yields obtained from the DataStream are used in implied volatility calculations.

We first calculate implied volatility for each trade in a volume bucket, then average these implied volatilities for each moneyness category. We then calculate two measures of slope taking differences of average implied volatilities as follows:

$$\text{Slope}_1 = IV_{ATMP} - IV_{ATMC} \qquad (1)$$

$$\text{Slope}_2 = IV_{OTMP} - IV_{ATMC}$$

where IV_{ATMP} and IV_{OTMP} are implied volatilities of ATM and OTM puts respectively and IV_{ATMC} is implied volatility of ATM calls. Figure 2 graphs the average implied volatilities of all traded call and put options in 2006 as a function of moneyness level. The average of the volatility skews has a smirk shape during 2006 in line with previously documented patterns. As observed in the figure average implied volatility of put options is higher than that of call options. This is intuitive as demand for put options is higher and they are traded more.

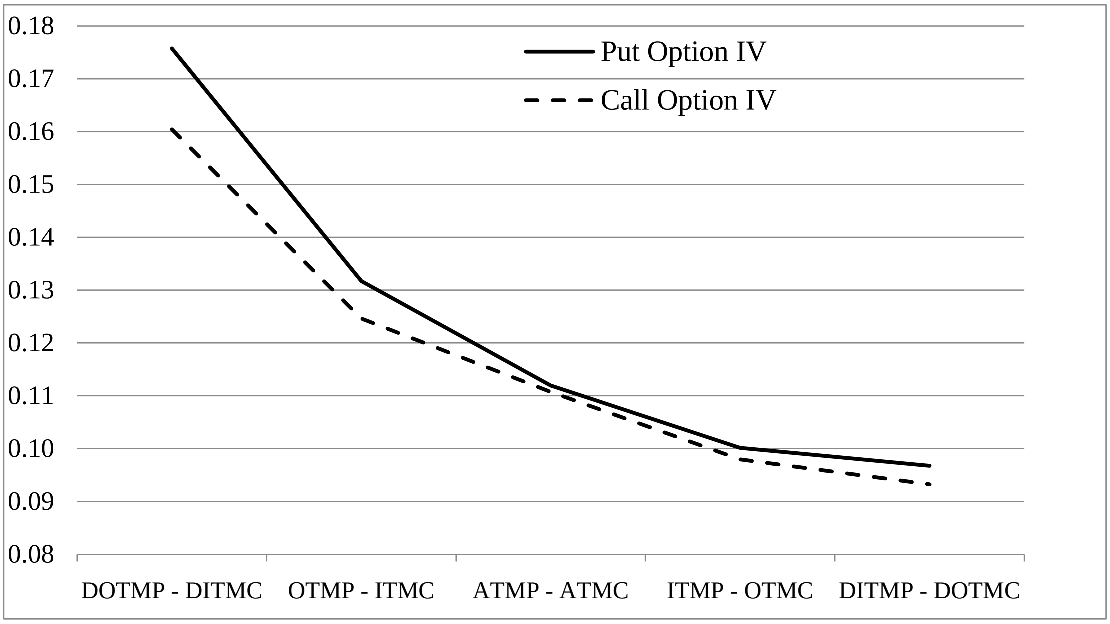

Figure 2. Option Implied Volatilities. Figure plots the average implied volatilities of call and put options as a function of moneyness for the SPX Options during 2006 using high frequency data.

2.2.2.2 Liquidity and Transaction Costs

There are numerous studies on the effects of liquidity on stock market, but research is limited for the derivatives market. Moreover, the effect of liquidity on option prices is not easy to interpret as investors hold both short and long positions. In an option pricing model, Cetin et al. (2007) model liquidity costs as a stochastic supply curve with the underlying asset price depending on order flow and suggest that liquidity costs may be partially responsible for the implied volatility "smile". Chou, Chung, Hsiao and Wang (2011) show that liquidity affects both the level and slope of implied volatility curve for 30 component stocks in the Dow Jones Industrial Average (DJIA). Specifically they find that when the option market is more liquid (lower bid-ask spreads for options), the implied volatility curve is steeper. Deuskar, Gupta and Subrahmanyam (2011) use bid-ask spreads to proxy for illiquidity and find that illiquid interest rate options trade at higher prices relative to more liquid options in the over-the-counter market. Feng, Hung and Wang (2014) provide evidence supporting the notion that option pricing models must incorporate liquidity risks. In this respect, we try to control effects of liquidity in our sample by choosing short-term options which are most liquid. Moreover, sampling by equal volume buckets also helps us to control for liquidity effects since a widely used measure of liquidity in options market is the log of number of option contracts for an interval and volume buckets include same fixed number of contracts.

Using daily S&P 100 Index option prices, Longstaff (1995) shows that market frictions such as transaction costs also play a major role on option prices besides market illiquidity. Pena et al (1999) find that transactions costs estimated by daily average relative bid-ask spread of options, significantly affect the shape of the implied volatility functions. Ederington and Guan (2002) also present evidence that transaction costs related to the construction of the delta neutral portfolio cause volatility smiles. As a proxy for transaction costs, for each transacted option, we calculate a relative bid-ask spread, namely bid-ask spread divided by an option’s mid quote as in Amihud and Mendelson (1986). We then calculate an average relative bid-ask spread for each moneyness category in a volume bucket. Relative bid-ask spread is also considered a good proxy for liquidity.

2.2.2.3 Momentum

According to market momentum hypothesis, if past returns are positive, investors expect future stock returns to be positive and they will tend to buy call options on the market index. Similarly, if past returns are negative, investors will buy put options. High demand for call (put) options will create an upward pressure on call (put) prices. Pena et al. (1999) find that market momentum is a determinant for the level of implied volatility function for Spanish IBEX-35 Index options. They proxy momentum with log of the ratio of the three-month moving average of value weighted IBEX to its current level. Amin, Coval and Seyhun (2004) also find that option prices depend on stock market momentum. They observe that when stock returns decline, call-smile more than doubles and put smile more than triples. The effect is visible for at-the-money options but higher for out-of-the money options. They conclude that even though market momentum seems to affect the volatility smiles, it does not completely explain volatility smiles. We include momentum in our set of explanatory variables and calculate daily index return on a rolling window basis using thirteen volume buckets.

2.2.2.4 Time to maturity and market uncertainty

Pena et al. (1999) find that option's time-to-expiration and market uncertainty are also important variables that explain the smile of implied volatility function of Spanish IBEX-35 Index options. In this respect, we include time to maturity as an explanatory variable since volatility skew of S&P 500 Index options may also be changing throughout option's life. Option's time to maturity is the annualized number of calendar days between the trade date and the expiration date. Another variable we include in the analysis is market uncertainty about the return of S&P 500 Index and we proxy it with daily realized volatility which is the sum of squared five-min returns during each day (Andersen, Bollerslev, Diebold and Labys, 2001). Alternatively we use VIX as a proxy for market uncertainty.

2.2.2.5 Net Buying Pressure

Bollen and Whaley (2004) define Net Buying Pressure (NBP) as the difference between the number of buyer-motivated contracts and the number of seller-motivated contracts traded and show that NBP, especially for index puts, affect shape and movement of implied volatility function for S&P 500 index options. They calculate NBP daily for each options series, multiply it by the absolute value of the option's delta and standardize it with volume. In a similar fashion, we calculate NBP for each moneyness category in a volume bucket and include it in our analysis with other possible determinants of slope of implied volatility skew of S&P 500 options.

In order to calculate NBP, we first need to know which trades are buyer motivated and which trades are seller motivated. We apply widely used Lee and Ready (1991) algorithm to classify trades. According to this algorithm, transactions that occur at prices higher (lower) than the quote midpoint are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals the quote midpoint but is higher (lower) than the previous transaction price are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals both the quote midpoint and the previous transaction price but is higher (lower) than the last different transaction price are classified as being buyer-initiated (seller-initiated). Table II shows the distribution of buyer and seller motivated trades in our sample. For transactions 53.2% are buys and 45.5% are sells. We discard unidentified trades which constitute 1.3% of the population.

Once we have identified buyer and seller motivated trades, we calculate NBP using aggregate volume of all options as well as using volume of call and put option series separately. As defined previously, NBP is the difference between buyer motivated and seller motivated trades. We calculate NBP for each moneyness category in a volume bucket. Table III shows NBP for S&P 500 Index options in our filtered sample in terms of moneyness category. In line with prior evidence, put option trading is much higher than index call option trading. We observe that trading is mainly concentrated on ATM, OTM and DOTM options.

Table II

Distribution of Buyer/Seller Motivated S&P 500 Index Option Trades

Table presents the distribution of buyer/seller motivated S&P 500 Index options traded on Chicago Board Options Exchange in 2006 subject to filtration discussed in Data section. We use Lee and Ready (1991) algorithm to classify trades. According to this algorithm, transactions that occur at prices higher (lower) than the quote midpoint are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals the quote midpoint but is higher (lower) than the previous transaction price are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals both the quote midpoint and the previous transaction price but is higher (lower) than the last different transaction price are classified as being buyer-initiated (seller-initiated). We discard unidentified trades which constitute 1.3% of the population.

Identification Type	Number of Trades	Prop. of Total
Buy	256,332	53.2%
Sell	219,081	45.5%
Unidentified	6,317	1.3%
Total	481,730	100.0%

Table III

Summary of Net Buying Pressure for S&P 500 Index Options

Table presents the distribution of buyer/seller motivated S&P 500 Index options traded on Chicago Board Options Exchange in 2006 subject to filtration discussed in Data section according to moneyness categories. Moneyness category definitions are as in Table I. *Net* is the difference between buyer and seller motivated trades.

	Category	Buy	Sell	Net	Total	Prop. of Total (%)
CALLS	DITMC	195,785	114,15	81,635	309,935	0.7
	ITMC	543,831	543,418	413	1,087,249	2.5
	ATMC	2,446,186	2,249,534	196,652	4,695,720	10.9
	OTMC	2,010,184	1,632,883	377,301	3,643,067	8.5
	DOTMC	2,576,943	2,593,281	-16,338	5,170,224	12.0
	TOTAL	7,772,929	7,133,266	639,663	14,906,195	34.7
PUTS	DITMP	48,866	15,012	33,854	63,878	0.1
	ITMP	167,299	213,136	-45,837	380,435	0.9
	ATMP	2,383,708	2,229,217	154,491	4,612,925	10.7
	OTMP	3,899,926	3,492,139	407,787	7,392,065	17.2
	DOTMP	7,782,305	7,810,069	-27,764	15,592,374	36.3
	TOTAL	14,282,104	13,759,573	522,531	28,041,677	65.3
ALL		22,055,033	20,892,839	1,162,194	42,947,872	100.0

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2.2.2.6 Volume-Synchronized Probability of Informed Trading (VPIN)

We further investigate the role of demand and supply for different option series on slope of implied volatility skew. Since level of private information and adverse selection risk are key factors for market makers' portfolio rebalancing and supply, a metric that measures these may be an important determinant of implied volatility skew We use a new metric, VPIN, introduced by Easley et al (2012), to assess the level of informed trading and adverse selection risk of market makers. Informed trading for index options may arise if investors learn anything related to the macroeconomic announcements before the release time. Private information may also arise from heterogeneous interpretations of public information (Green, 2004). Investors who are credited with superior analytical skills or who are using superior models are likely to better process information. Private information for stock index options arises, because, even though everybody sees the same set of public news, their interpretation of the news may differ. A public news event can cause buy and sell decisions at the same time if investors use different models and disagree about the interpretation of the news. Kandel and Pearson (1995) also provide empirical evidence against the assumption that agents interpret public information identically.

VPIN measures the level of informed trading or the so-called order flow toxicity based on order imbalance and trade intensity in the market. Toxicity refers to the adverse selection risk of market makers and uninformed investors or risk of loss in trading with better informed parties. Informed traders are expected to trade on one side of the market and cause unbalanced volume. If market makers sense that order flow is toxic then they either cease or reduce their market making activities. In case they choose to continue to provide liquidity to the market, they charge higher prices for increased risk. Therefore, we hypothesize that there will be higher variability in prices and movement in slope, associated with increases in VPIN.

VPIN is based on the imbalance between buy and sell orders for each volume bucket during a sample window for all traded options. If we let $\tau = 1, \ldots n$ be the index of equal volume buckets, then a VPIN value for each volume bucket is calculated as follows:

$$VPIN \approx \frac{\sum_{\tau=1}^{n} \left| V_{\tau}^{S} - V_{\tau}^{B} \right|}{nV} \qquad (2)$$

where V is the constant bucket size and equal to 1/13th of the average daily volume in our sample, V_{τ} are the equal volume buckets for $\tau = 1, \ldots 13$ per day, V_{τ}^{S} is the volume classified as sell, V_{τ}^{B} is the volume classified as buy, and 'n' is length of the sample window or the number of buckets used to approximate the expected trade imbalance and intensity. VPIN is estimated on a rolling basis. This rolling calculation makes VPIN highly auto correlated but dropping buckets along the calculation avoids long memory in the process. If we let rolling window sample size n to be 5, then when sixth bucket is filled, bucket one is dropped and the new VPIN metric is calculated based on bucket two through six. VPIN value of the 6th bucket is independent from the VPIN value of the first bucket. If we let n to be 13, then this is equivalent to calculating a daily VPIN. Since we are working with high frequency data we want VPIN metric to be updated intraday and we use n as 5. We have an average of 13

VPIN values per day but on very active days the VPIN metric is updated much more frequently than on less active days.

VPIN has two advantages compared to PIN measure (Easley, Kiefer, O'hara and Paperman, 1996) which has been widely used in the literature as a proxy for the level of informed trading in markets. First, we do not have to estimate unobserved parameters for VPIN. Second, there are also criticisms against PIN for being a proxy for only illiquidity effects and not asymmetric information. (Duarte and Young, 2009; Akay, Cyree, Griffiths, and Winters, 2012). VPIN is less prone to infrequent trading since equal volume buckets are used. Table IV presents the summary statistics for our variables in volume time. Average VPIN is 0.38 with a maximum of 1 and a minimum of 0.04. Average implied volatility is 10% for calls and 17% for puts. Average VIX is 13.09% annually.

2.3 Empirical Results

The objective of this section is to explore the linkage between the variables discussed in the prior section and changes in slope of implied volatility skew of S&P 500 options. We start the analysis by conducting the Augmented Dickey-Fuller stationarity tests on our variables. We are able to reject the existence of a unit root for all of our variables and first difference of VIX. Observation of the ACF reveals that change in slope is highly auto-correlated and we include first lag of slope as an independent variable in the regression.

Table IV

Summary Statistics

Table lists the summary statistics for our variables. *VPIN* is the order flow toxicity metric calculated as in Equation (3). *Calls NBP (Puts NBP)* is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for calls (puts). *Calls Imp. Volatility (Puts Imp. Volatility)* is the average of implied volatilities for calls (puts). *Calls Spread (Puts Spread)* is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote for calls (puts). *Slope* is one of the three measures of slope defined in Equation (1). *Index* is index level. *Index Return* is the index return computed from volume bar n-13 to n-1. *Real. Volatility* is realized volatility which is the sum of squared five-min returns during each day. *VIX* is the CBOE's volatility index for the S&P 500 index return.

Variable Name	Min	Median	Max	Mean	Std. Dev.	Skewness	Kurtosis
VPIN	0.04	0.34	1.00	0.38	0.19	0.80	3.21
Calls NBP	-5678.46	15.17	16311.92	81.25	1201.35	2.01	26.36
Calls Imp. Volatility	0.07	0.10	0.18	0.10	0.02	0.93	3.51
Calls Spread	0.03	0.15	1.43	0.17	0.09	3.97	34.09
Puts NBP	-32395.32	45.15	6989.40	45.71	1224.09	-9.22	230.07
Puts Imp. Volatility	0.09	0.13	0.27	0.14	0.03	1.06	3.69
Puts Spread	0.04	0.13	0.68	0.14	0.06	3.02	16.45
ATM Calls NBP	-4128.43	0.54	9320.21	26.62	685.71	0.99	19.47
ATM Calls Spread	0.01	0.07	0.32	0.07	0.02	1.69	12.86
ATM Puts NBP	-32396.52	1.22	4725.65	16.15	998.57	-17.22	517.47
ATM Puts Spread	0.01	0.07	0.22	0.07	0.02	0.92	6.92
OTM Puts NBP	-3088.33	2.46	3232.77	35.80	478.48	0.16	9.20
OTM Puts Spread	0.02	0.10	0.31	0.11	0.03	1.09	7.10
DOTM Puts NBP	-2164.55	0.00	2373.45	-5.13	253.32	-0.42	14.36
DOTM Puts Spread	0.03	0.22	1.06	0.23	0.09	2.08	10.96
$Slope_1$	-0.07	0.00	0.04	0.00	0.01	-2.11	26.78
$Slope_2$	-0.05	0.02	0.09	0.02	0.01	0.87	5.43
Index	1219.73	1295.20	1431.59	1308.75	52.32	0.82	2.56
Index Return	-0.02	0.00	0.03	0.00	0.01	0.09	4.71
Real. Volatility	0.00	0.08	0.43	0.09	0.05	2.75	13.41
VIX	9.44	12.07	22.99	13.09	2.58	1.10	3.63

To assess the relation between slope and variables discussed above, we estimate the following regression with Newey-West corrected standard errors:

$$\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_{\mathrm{n}} + \beta_4 Spread_{\mathrm{n}} + \beta_5 RV_{\mathrm{n}} + \beta_6 NBP_{\mathrm{n}} + \beta_7 VPIN_{\mathrm{n}} + e_n \qquad (3)$$

where $\Delta Slope_n$ is change in one of the three measures of slope defined in Equation (1) from volume bar *n-1* to *n*. R_n is the index return computed from volume bar n-13 to n-1 for the momentum effect. $Time_n$ is option's annualized time to maturity. $Spread_n$ is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and is calculated for calls and puts separately for each moneyness category. RV_n is realized volatility which is the sum of squared five-min returns during each day. NBP_n is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for each moneyness category of calls and puts separately. NBP variables vary in different regressions depending on the slope measure. $VPIN_n$ is the metric for probability of informed trading and calculated as in Equation (2).

Table V displays the results of regression in Equation (3) and show that all of our variables except momentum seem to contribute to the variability of slope of implied volatility skew of S&P 500 Index Options. Pena et al. finds a weak relation between market momentum and degree of curvature of the smile and in our analysis the effect of momentum on slope is not significant. In line with Pena et al.'s findings for Spanish Index options we find that change in slope of S&P 500 Index options is related to transactions costs represented by bid-ask spreads, time to expiration of the options and volatility of the index. The lagged change in slope is negatively and significantly related to current change in both measures of slope. This is in line with limits to arbitrage theorem which suggests that as market makers rebalance their portfolios, prices reverse to their previous levels gradually.

In line with Bollen and Whaley (2004), NBP of options significantly affect slope. Both measures of slope, the coefficient of NBP of ATM calls is significant and negative. NBP of ATM (OTM) puts is significantly and positively related to $Slope_1$ ($Slope_2$). Besides these variables, we find a significant relation between VPIN and slope. The relation is positive for both measures of slope. This implies that the higher the level of private information and order flow toxicity in the market the more asymmetrically the OTM and ATM puts are valued in the market relative to ATM calls.

Informed traders try to time their trades at times of high level of trading and liquidity and macroeconomic announcements provide an avenue for investors to trade more aggressively on their private information. If VPIN captures the probability of informed trading well, then it would be interesting to see the relation between VPIN and slope at macroeconomic announcement times. The macroeconomic announcement

Table V

Determinants of Slope of S&P 500 Index Options Skew

Table presents the regression results of $\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_{\mathrm{n}} + \beta_4 Spread_{\mathrm{n}} + \beta_5 RV_{\mathrm{n}} + \beta_6 NBP_{\mathrm{n}} + \beta_7 VPIN_{\mathrm{n}} + e_n$ where $\Delta Slope_n$ is change in one of the two measures of slope defined in Equation (1) from volume bar *n-1* to *n*. R_n is the index return computed from volume bar n-13 to n-1for the momentum effect. $Spread_n$ is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and RV_n is realized volatility which is the sum of squared five-min returns during each day. $Time_n$ is option's annualized time to maturity. NBP_n is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for each moneyness category. $VPIN_n$ is the metric for probability of informed trading and calculated as in Equation (2). ***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively.

	Δ Slope₁			**Δ Slope₂**		
	Coefficient	**t-value**		**Coefficient**	**t-value**	
Intercept	-0.003	-3.334	***	-0.006	-5.751	***
$\Delta slope_{n-1}$	-0.346	-20.466	***	-0.379	-22.569	***
R	0.025	1.465		0.002	0.091	
Time	0.005	0.915		0.016	2.513	**
Atm Call Spread	0.004	0.888		-0.007	-1.118	
Atm Put Spread	0.016	2.860	***			
Otm Put Spread				0.040	8.927	***
RV	0.004	1.900	*	0.002	0.617	
Atm Call NBP	-0.014	-7.476	***	-0.010	-4.442	***
Atm Put NBP	0.015	7.787	***			
Otm Put NBP				0.014	4.205	***
VPIN	0.001	2.575	***	0.002	2.438	**

timings, realizations and survey expectations are obtained from Bloomberg. Most of the announcements are monthly but initial jobless claims announcement is weekly and we also have a number of quarterly announcements. Table VI lists the macroeconomic announcements that we include in our analysis. We include 23 macroeconomic announcements and most of the announcements are monthly but initial jobless claims announcement is weekly and we also have a number of quarterly announcements.

We first visually examine behavior of slope and VPIN around macroeconomic announcements. We calculate the averages of slope and VPIN for each volume bar corresponding to the announcement time t, and up to 15 pre-announcement and post-announcement volume bars from January through December in 2006. Figures 3 and 4 plot the averages. Figure 3 shows that $Slope_2$ drops sharply in response to an announcement release but drop is not that significant $Slope_1$. In Figure 4, we observe that VPIN calculated over a window size of 5, starts to decrease 5 volume bars before the announcement and increases afterwards. Before the announcement, we observe a tranquil period for informed traders in options market, which could be due to investors' tendency to wait for the releases and postpone their trades. Informed trading activity increases within nine volume bars following an announcement. As most of the announcements coincide with market opening, it is difficult to anticipate the response time of the informed traders to the announcement release, nine volume bars might correspond to a very short period of response time.

We continue our analysis with adding one more variable to the regression equation (3) to test the relation between VPIN and implied volatility skew at macroeconomic announcements times. We observe that for $Slope_2$ the impact of News dummy is stronger than the impact of VPIN. When there is a macroeconomic announcement with information resolution there is a decrease in $Slope_2$.

Table VI

Macroeconomic Announcements

Table lists the macroeconomic announcements used in this study along with the category, timing in EST, source, frequency. Abbreviations are Investors Business Daily (IBD), Automatic Data Processing (ADP), Federal Reserve Board (FRB), Bureau of Labor and Statistics (BLS), Bureau of Economic Analysis (BEA), Bureau of the Census (BC), Conference Board (CB), US. Department of Labor (UDL), Institute for Supply Management (ISM), Federal Reserve Bank of Philadelphia (FRBP) and National Association of Realtors (NAR).

Macroeconomic Announcement	**Time**	**Source**	**Frequency**
ADP Employment Change	8:15	ADP	Five times
Unemployment Rate	8:30	BLS	Monthly
Initial Jobless Claims	8:30	UDL	Weekly
Consumer Price Index	8:30	BLS	Monthly
Unit Labor Costs	8:30	BLS	Eight times
GDP Price Index	8:30	BEA	Monthly
Producer Price Index	8:30	BLS	Monthly
Chicago Purchasing Manager	10:00	ISM	Monthly
Consumer Confidence	10:00	CB	Monthly
IBD/TIPP Economic Optimism	10:00	IBD	Six times
Philadelphia Fed.	12:00	FRBP	Monthly
Index of Leading Indicators	10:00	CB	Monthly
Housing Starts	8:30	BC	Monthly
Durable Goods Orders*	8:30	BC	Monthly
Factory Orders	10:00	BC	Monthly
Construction Spending	10:00	BC	Monthly
Business Inventories	10:00	BC	Monthly
Wholesale Inventories	10:00	BC	Monthly
Personal Income/Spending	8:30	BEA	Monthly
Retail Sales Less Autos	8:30	BC	Monthly
Capacity Utilization/Industrial Production	9:15	FRB	Monthly
Existing Home Sales	8:30	NAR	Monthly
New Home Sales	10:00	BC	Monthly

*When there is also a GDP announcement that day, the durable goods orders announcement is made at 10:00 AM

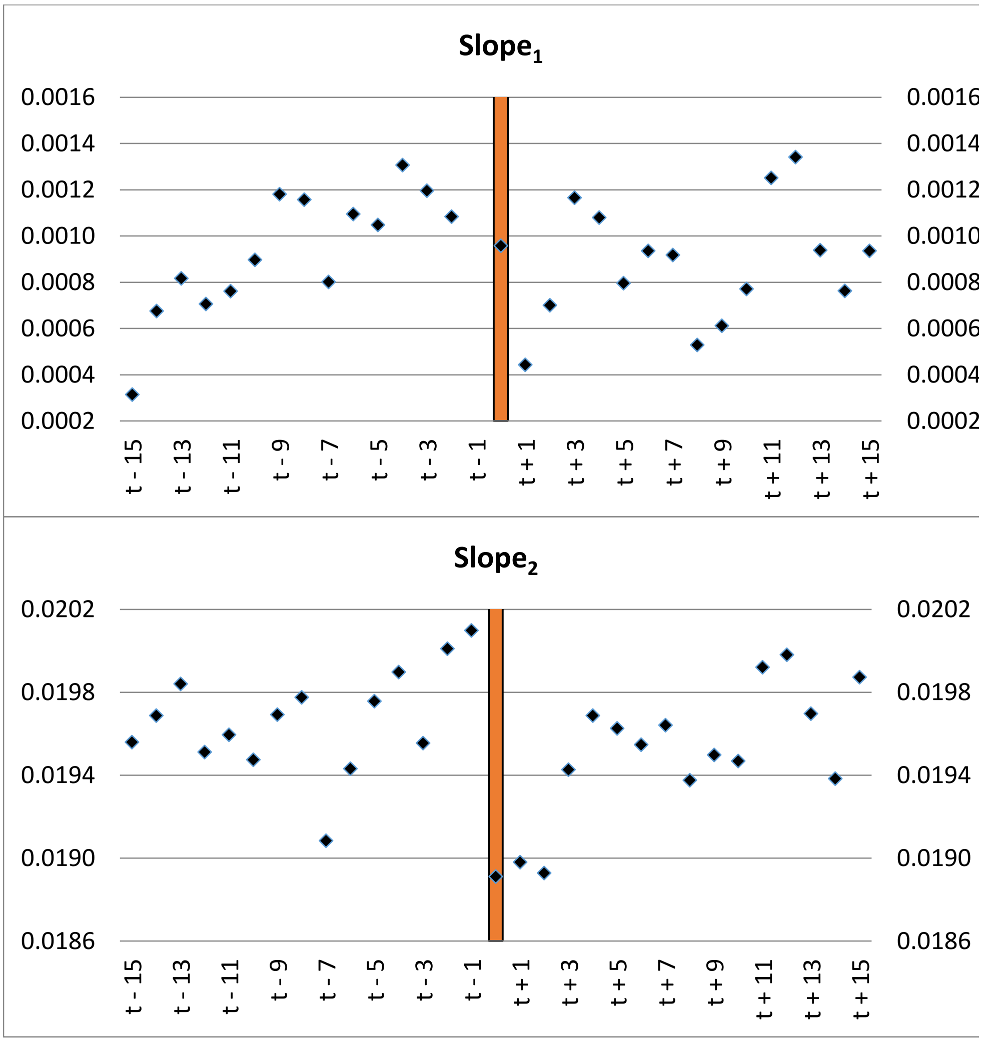

Figure 3. Behavior of Slope at Announcements in Volume Time. Figure plots the average of slope for each volume bucket corresponding to the announcement time t during 2006. Pre-announcement and post-announcement means of slope are also included up to 15 volume buckets.

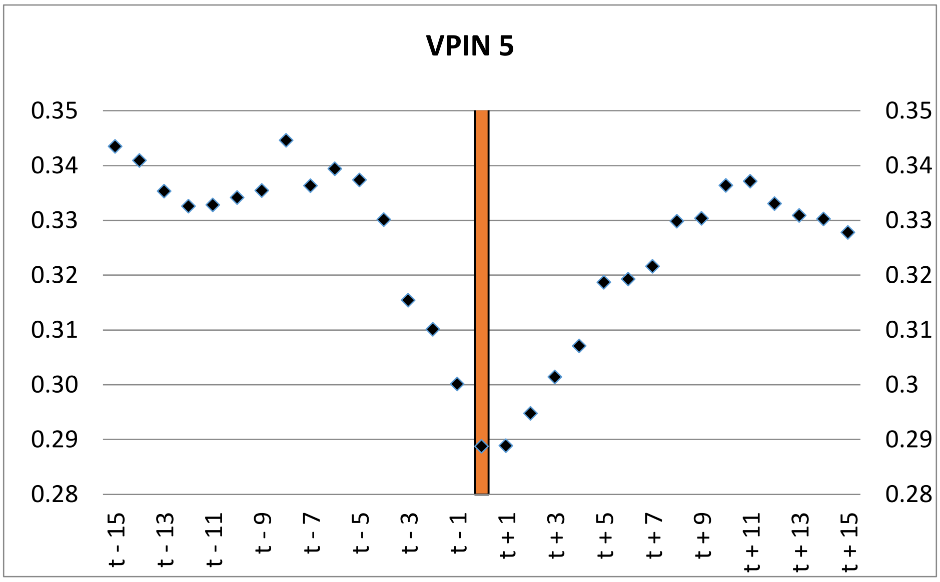

Figure 4. Behavior of VPIN at Announcements in Volume Time. Figure plots average of VPINs for each volume bucket corresponding to the announcement time t during 2006. Pre-announcement and post-announcement means of VPIN are also included up to 15 volume buckets. Length of the sample window that VPIN is updated on a rolling basis is 5.

We also look into the surprise component of the announcement and analyze whether there is a stronger impact on slope when the surprise is bigger. The surprise component is defined as the difference between the announced figure and survey expectations. Surprises are assumed to be stochastic since they are related to the incorrect anticipation by the market participants. To allow for meaningful comparisons of coefficients across different announcements, we standardize news by the standard deviation of the surprise component for different announcements as in Andersen, Bollerslev, Diebold and Vega (2003, 2007). The standardized news for announcement

Table VII

VPIN and Slope at Macroeconomic Announcement Times

Table presents the regression results of $\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_{\mathrm{n}} + \beta_4 Spread_{\mathrm{n}} + \beta_5 RV_{\mathrm{n}} + \beta_6 NBP_{\mathrm{n}} + \beta_7 VPIN_{\mathrm{n}} + \beta_8 News_{\mathrm{n}} + \beta_9 (News_{k,t} * VPIN)_{\mathrm{n}} + e_n$ where $\Delta Slope_n$ is change in one of the two measures of slope defined in Equation (1) from volume bar *n-1* to *n*. R_n is the index return computed from volume bar n-13 to n-1for the momentum effect. $Spread_n$ is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and RV_n is realized volatility which is the sum of squared five-min returns during each day. $Time_n$ is option's annualized time to maturity. NBP_n is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for each moneyness category. $VPIN_n$ is the metric for probability of informed trading and calculated as in Equation (2). $News_n$ is a dummy variable that takes one for the volume bucket n that includes a macroeconomic announcement and zero otherwise ***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively.

	Δ Slope$_1$			**Δ Slope$_2$**		
	Coefficient	**t-value**		**Coefficient**	**t-value**	
Intercept	-0.003	-3.223	***	-0.006	-5.515	***
Δslope$_{n-1}$	-0.345	-20.414	***	-0.379	-22.597	***
R	0.025	1.485		0.004	0.167	
Time	0.005	0.908		0.016	2.510	**
Atm Call Spread	0.005	0.897		-0.007	-1.113	
Atm Put Spread	0.016	2.872	***			
Otm Put Spread				0.040	9.053	***
RV	0.004	1.897	*	0.001	0.588	
Atm Call NBP	-0.014	-7.476	***	-0.010	-4.444	***
Atm Put NBP	0.015	7.789	***			
Otm Put NBP				0.014	4.273	***
VPIN	0.001	2.290	**	0.001	1.745	*
News	-0.001	-0.677		-0.003	-2.268	**
News*VPIN	0.000	0.138		0.004	1.145	

k at time t, $Surprise_{k,t}$, is defined as follows:

$$Surprise_{k,t} = \frac{Actual_{k,t} - Expectation_{k,t}}{\widehat{\sigma}_k} \qquad (4)$$

where $Actual_{k,t}$ refers to the announced value and $Expectation_{k,t}$ refers to the market's expectation, for macro fundamental k at time t. $\widehat{\sigma}_k$ refers to the sample standard deviation of the surprise component, the difference between $Actual_{k,t}$ and

$Expectation_{k,t}$ is constant for any macro fundamental k. Table VIII reports the results of the regression equation 3 with an interaction term of $Surprise_{k,t}$ with $VPIN_n$. We see that the effect of macroeconomic surprise dominates and the interaction term is insignificant for $Slope_2$.

2.4 Conclusion

This paper examines the high frequency characteristics of S&P 500 index options' implied volatility skew. Slope of implied volatility skew is a good proxy for jump risk and investor risk aversion. In an attempt to explain changes in implied volatility skew, we examine a range of microstructure variables including the level of order flow toxicity in the market using VPIN metric. Our analysis is carried out in equal volume bars that match the arrival rate of information to the market. Results document a statistically significant relation between slope and order flow toxicity even after controlling for liquidity, volatility and momentum effects, transaction costs and net buying pressure. In this respect, option pricing models may benefit from incorporating a measure of market makers' adverse selection risk.

We further analyze the relation between VPIN and slope at macroeconomic announcement times. Informed traders try to time their trades at times of high level of trading and liquidity and macroeconomic announcements provide an avenue for investors to trade more aggressively on their private information. We find that

Table VIII

VPIN and Slope with Macroeconomic Announcement Surprises

Table presents the regression results of $\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_\mathrm{n} + \beta_4 Spread_\mathrm{n} + \beta_5 RV_\mathrm{n} + \beta_6 NBP_\mathrm{n} + \beta_7 VPIN_\mathrm{n} + \beta_8 Surprise_\mathrm{n} + \beta_9 (Surprise_{k,t} * VPIN)_\mathrm{n} + e_n$ where $\Delta Slope_n$ is change in both measures of slope defined in Equation (1) from volume bar *n-1* to *n*. R_n is the index return computed from volume bar n-13 to n-1for the momentum effect. $Spread_n$ is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and RV_n is realized volatility which is the sum of squared five-min returns during each day. $Time_n$ is option's annualized time to maturity. NBP_n is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta standardized by volume for each moneyness category. $VPIN_n$ is the metric for probability of informed trading and calculated as in Equation (2). $Surprise_{k,t}$ is defined as in Equation (4). ***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively.

	Δ Slope$_1$			**Δ Slope$_2$**		
	Coefficient	**t-value**		**Coefficient**	**t-value**	
Intercept	-0.003	-3.190	***	-0.006	-5.573	***
$\Delta slope_{n-1}$	-0.345	-20.348	***	-0.379	-22.487	***
R	0.028	1.630		0.004	0.175	
Time	0.005	0.914		0.017	2.538	**
Atm Call Spread	0.005	0.942		-0.007	-1.057	
Atm Put Spread	0.016	2.902	***			
Otm Put Spread				0.040	9.067	***
RV	0.003	1.777	*	0.001	0.455	
Atm Call NBP	-0.014	-7.355	***	-0.011	-4.566	***
Atm Put NBP	0.015	7.800	***			
Otm Put NBP				0.014	4.146	***
VPIN	0.001	2.201	**	0.001	1.855	*
Surprise	-0.001	-1.562		-0.002	-2.467	**
Surprise*VPIN	0.001	0.687		0.003	1.297	

that the effects of uncertainty resolution and decrease in information asymmetry effects are dominant when there is a macroeconomic announcement and when the surprise component of the announcement is higher.

A clearer comprehension about the factors that affect the slope is important for developing new option pricing models and devising proper hedging and investment strategies. Our results justify why traders shall closely monitor slope to understand how jump risk and risk aversion are evolving during a trading day.

CHAPTER III

IMPACT OF MACROECONOMIC ANNOUNCEMENTS ON IMPLIED VOLATILITY SLOPE OF SPX OPTIONS AND VIX

The Black-Scholes Option Pricing Model presumes that for the same underlying asset, the implied volatilities shall be constant in the same maturity category across different strike prices. However, empirical literature documents that options on the same underlying with the same maturity dates have different implied volatilities across different strike prices. This anomaly is known as the volatility skew and takes the shape of a smile or a smirk depending on the instrument. Option traders and financial analysts closely monitor the volatility skew as they believe that it carries important information regarding the market structure and the risk aversion of the participants in the market. This paper examines the impact of macroeconomic announcements on the observed implied volatility skew of S&P 500 index options and VIX in a high-frequency setting.

There have been various studies that investigate the effects of macroeconomic news on financial markets but not in the context of implied volatility skew. Ederington and Lee (1996) are the first to study the impact of macroeconomic announcements on option implied volatility of T-bonds and foreign exchange.

Kearney and Lombra (2004) find a significant positive relation between the CBOE volatility index VIX, and unanticipated changes in employment, but not inflation. Baba and Sakurai (2011) investigate whether macroeconomic variables are leading indicators of regime shifts in the VIX and find that term spreads predict the shift from tranquil to the turmoil regime. Füss et al. (2011) focus only on Gross Domestic Product, Producer Price Index and Consumer Price Index announcements and find that VIX drops on announcement days. This study covers a larger range of macroeconomic announcements and is able to observe the intraday behavior of VIX.

A related strand of literature investigates the effects of monetary policy on stock returns and volatility. Chen and Clements (2007) and Vähämaa and Äijö (2011) investigate the behavior of VIX around US monetary policy announcements and find that implied volatility generally decreases after FOMC meetings. Gospodinov and Jamali (2012) conduct a monthly analysis of the relation between Federal funds rate surprises and implied volatility and volatility risk premium controlling for non-farm payroll employment, consumer price inflation and industrial production announcements. They find that surprises in Fed funds rates and both inflation and industrial growth affect VIX significantly in monthly regressions. Rosa (2011) investigates the effects of Fed's monetary surprises on US stock and volatility indices in a high frequency setting. He finds that the surprise change to the current target federal funds rate significantly affects all indices and the surprise component of Fed's statements affect all but VIX.

This study analyzes the effect of 23 macro announcements, grouped under categories of inflation, investment, employment, real activity and forward-looking, on 2006 high-frequency behavior of VIX and slope of S&P 500 index options. We also analyze the surprises contained in the announcements by computing the difference between the announced and expected figures. We find that macroeconomic announcement impact is statistically significant on VIX for almost every announcement category and at a lesser extent on slope. To study the asymmetric volatility we further categorize information contained in macroeconomic announcements as good or bad. We find evidence that good and bad announcements asymmetrically affect slope of implied volatility smirk of S&P 500 Index options and VIX.

The remainder of the paper is organized as follows. Section one describes the data and variable construction. Section two presents the results of the analysis of the effects of macro announcements on implied volatility skews and VIX. Section three concludes.

3.1 Data filtering and analysis

The data consists of tick-by-tick data of S&P 500 Index (SPX) option contracts and is obtained from Berkeley Options Database for a total of 250 trading days in 2006[4]. The dataset is derived from the Market Data Report (MDR file) of the Chicago Board Options Exchange (CBOE) and includes time-stamped (in seconds) option trades and quotes (options of all strikes and maturities) including expiration date, put – call code, exercise price, bid and ask prices and contemporaneous price of the underlying S&P 500 Index. Daily SPX dividend yields and U.S. T-Bill Secondary Market Rates are obtained from the DataStream database. For implied volatility calculations, we use 1-month, 3-month, 6-month, and 1-year nominal U.S. T-Bill Secondary Market Rates and apply cubic spline polynomial interpolation to match maturity dates of options.

Tick by tick options data is filtered based on maturity, no-arbitrage lower option boundaries and for obvious reporting errors and outliers. In order to avoid implied volatilities that are likely to be measured with error, only options with bid prices greater than zero are used[5]. Put-Call parity violations are not filtered as they might contain evidence related to the trading activity of informed traders (Cremers and Weinbaum, 2010). We include options that have maturities between 15 and 45 trading days since these are the most liquid options. This study does not include options that have maturities shorter than 15 days, as shorter term options have relatively small time premiums and are substantially unreliable when calculating option implied volatilities (Dumas et. al., 1998).

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[4] Sample data does not coincide with US financial crisis of 2007-2009.

[5] In a same manner, but a bit different approach, some authors use options with bid-ask midpoints higher than 0.125 or 0.25.

The macroeconomic announcement timings, realizations and survey expectations are obtained from Bloomberg. Most of the announcements are monthly but initial jobless claims announcement is weekly and we also have a number of quarterly announcements. We group macroeconomic announcements under five categories: inflation, investment, employment, real activity and forward-looking.

Macroeconomic announcements are also categorized as good and bad news according to their surprise component as in Bauwens, Omrane, and Giot (2005). For a macroeconomic figure, if the realized value is higher than the expected value in surveys and stimulates economic growth then the news is classified as good. If the news implies economic slowdown then it is classified as bad. If the figure is an inflation related news and the actual is higher than expected then the news is classified as bad news. Table I provides the frequency, source, timing and categorization for the list of macroeconomic announcements.

The surprise component is defined as the difference between the announced figure and survey expectations. Surprises are assumed to be stochastic since they are related to the incorrect anticipation by the market participants. To allow for meaningful comparisons of coefficients across different news categories, we standardize news by the standard deviation of the surprise component for different announcements as in Andersen et al. (2007). The standardized news for announcement k at time t, $S_{k,t}$, is defined as follows:

Table I

Macroeconomic Announcements

Table lists the macroeconomic announcements used in this study along with the category, timing in EST, source, frequency. We separate good and bad announcements by comparing realized and expected numbers. If the realized value is higher than the expected value in surveys and stimulates economic growth then the news is classified as good. If the news implies economic slowdown or higher inflation then it is classified as bad. Abbreviations are Investors Business Daily (IBD), Automatic Data Processing (ADP), Federal Reserve Board (FRB), Bureau of Labor and Statistics (BLS), Bureau of Economic Analysis (BEA), Bureau of the Census (BC), Conference Board (CB), US. Department of Labor (UDL), Institute for Supply Management (ISM), Federal Reserve Bank of Philadelphia (FRBP) and National Association of Realtors (NAR).

Macroeconomic Announcement	**Time**	**Source**	**Frequency**	**Good**	**Bad**
Employment					
ADP Employment Change	8:15	ADP	Five times	-	+
Unemployment Rate	8:30	BLS	Monthly	-	+
Initial Jobless Claims	8:30	UDL	Weekly	-	+
Inflation					
Consumer Price Index	8:30	BLS	Monthly	-	+
Unit Labor Costs	8:30	BLS	Eight times	-	+
GDP Price Index	8:30	BEA	Monthly	-	+
Producer Price Index	8:30	BLS	Monthly	-	+
Forward-looking					
Chicago Purchasing Manager	10:00	ISM	Monthly	+	-
Consumer Confidence	10:00	CB	Monthly	+	-
IBD/TIPP Economic Optimism	10:00	IBD	Six times	+	-
Philadelphia Fed.	12:00	FRBP	Monthly	+	-
Index of Leading Indicators	10:00	CB	Monthly	+	-
Housing Starts	8:30	BC	Monthly	+	-
Investment					
Durable Goods Orders*	8:30	BC	Monthly	+	-
Factory Orders	10:00	BC	Monthly	+	-
Construction Spending	10:00	BC	Monthly	+	-
Business Inventories	10:00	BC	Monthly	-	+
Wholesale Inventories	10:00	BC	Monthly	-	+
Real Activity					
Personal Income/Spending	8:30	BEA	Monthly	+	-
Retail Sales Less Autos	8:30	BC	Monthly	+	-
Capacity Utilization/Industrial Production	9:15	FRB	Monthly	+	-
Other					
Existing Home Sales	8:30	NAR	Monthly	+	-
New Home Sales	10:00	BC	Monthly	+	-

*When there is also a GDP announcement that day, the durable goods orders announcement is made at 10:00 AM.

$$S_{k,t} = \frac{Actual_{k,t} - Expectation_{k,t}}{\hat{\sigma}_k} \qquad (1)$$

where $Actual_{k,t}$ refers to the announced value and $Expectation_{k,t}$ refers to the market's expectation, for macro fundamental k at time t. $\hat{\sigma}_k$ refers to the sample standard deviation of the surprise component, the difference between $Actual_{k,t}$ and $Expectation_{k,t}$ is constant for any macro fundamental k.

One of the problems of working with high frequency data is arrival of market ticks at random time. Regular time-series econometric tools which frequently use backward operators cannot be applied to irregularly spaced or inhomogeneous time series (Gencay et al., 2001). Traditional approach to this problem is to equally space time-series data and work with time bars. In order to homogenize time series data, high-frequency finance literature uses interpolation and aggregation. Aït-Sahalia, Mykland and Zhang (2005) note that sampling too frequently may not be optimal in the presence of market microstructure noise. Moreover, our trade data is not as frequent as quote data. Therefore, we choose subsampling frequency as thirty-min intervals.

Implied volatility calculations are conducted using Black and Scholes option pricing formula. We first calculate implied volatilities for the European-style S&P 500 index options for each moneyness category. Options are grouped in moneyness categories according to their deltas. A call option with Δ_{call}= 0.5 is treated as an

ATM call option. Similarly, a put option with $\Delta_{put} = -0.5$ is treated as an ATM put option. Although these options are not exactly ATM, they are very close to being ATM (Yan, 2011).

The slope measure is defined as the difference between ATM puts and calls as in Yan (2011):

$$S = v_{put}^{imp}(-0.5) - v_{call}^{imp}(0.5) \qquad (2)$$

Where implied volatilities of put and call options with deltas equal to Δ_{put} and Δ_{call} are denoted as $v_{call}^{imp}(\Delta_{call})$ and $v_{put}^{imp}(\Delta_{put})$ respectively. We standardize slope by dividing it to daily realized volatility to control for the fluctuations in slope related to the level of volatility.

3.1.1 Momentum and Liquidity Effects

According to market momentum hypothesis if past returns are positive, investors expect future stock returns to be positive and they will tend to buy call options on the market index. Similarly if past returns are negative, investors will buy put options. High demand for call (put) options will create an upward pressure on call (put) prices. Amin, Coval and Seyhun (2004) do find that option prices depend on stock market momentum. They find that when stock returns decline, call-smile more than doubles and put smile more than triples. The effect is visible for at the money options but higher for out of the money options. They conclude that even though market momentum seems to affect the volatility smiles, it does not completely explain

Table II

Summary Statistics

Table lists the summary statistics for our variables. *Slope* is slope of implied volatility skew of SPX options calculated as the difference between ATM calls and puts during 2006. *Std. Slope* is *Slope* divided by daily realized volatility. *IV* is the average of ATM call and put implied volatilities. *VIX* is the CBOE's volatility index for the S&P 500 index return.

	Slope	Std. Slope	IV	VIX
Min	-0.094	-24.467	0.021	0.094
Mean	0	0.081	0.116	0.135
Max	0.103	22.565	0.198	0.234
Std. Dev.	0.011	2.196	0.023	0.028
Skewness	0.958	1.422	0.871	0.010
Kurtosis	17.306	26.031	0.808	0.004

volatility smiles. Therefore we control for momentum or past stock return effects using lagged thirty-min returns. Literature also proposes liquidity as a possible determinant of implied volatility skew. Since we are using ATM options, liquidity is less of an issue in our analysis. Table II presents the summary statistics for our variables. Average annual implied volatility is 11.6% and VIX is 13.5%.

3.2 Empirical Results

The objective of the empirical analysis is to analyze whether macroeconomic announcements affect standardized implied volatility slope of S&P 500 options and VIX. We start the analysis by conducting the Augmented Dickey-Fuller stationarity tests on our variables. We are able to reject the existence of a unit root for standardized slope and first difference of VIX. Observation of the ACF reveals that standardized slope is highly auto-correlated and decays slowly for thirty-min data. Therefore we test for long memory in slope using the range over standard deviation (R/S statistic) and GPH test. Both methods confirm that long memory exists in the time-series of standardized slope. In this respect, we use fractional autoregressive integrated moving average (FARIMA) process to model the short run dynamics and long range dependence in time series of standardized slope simultaneously.

We first estimate the following regression to measure the response of standardized slope to macroeconomic announcement categories:

$$Std\ Slope_t = \alpha + \omega R_t + \sum_k \sum_p \beta_{k,p} D_{k,(t-p)} + e_t \qquad (5)$$

where $Std\ Slope_t$ is defined as the ratio of the difference between ATM put and call implied volatilities to daily realized volatility. The dependent variable is the residual from FARIMA model of standardized slope. We examine the intraday changes in standardized slope using thirty-min time intervals. For each time bar we calculate slope using the ATM call and put trades that are closest to the end of thirty-min time intervals. R_t is the index return computed from time interval t-16 to t-1 and included as a control variable for the momentum effect. $D_{k,t}$ is a dummy variable that takes one for the thirty-min interval t that includes a macroeconomic announcement that belongs to category k at time t and zero otherwise. Since the options market operates in CT, it is not open during macroeconomic announcements made at 8:30 am EST, $D_{k,t}$ takes one for the first thirty-min interval of that day.

Table III displays the results of regression in Equation (5) and show that investment, inflation and real activity announcement categories seem to have an impact on the slope of implied volatility skew of S&P 500 Index Options. Real activity category announcements seem to increase slope first and then cause a drop in slope in three and a half hours with higher statistical significance. Employment and forward-looking category announcements do not seem to be related to slope, with an exception of forward looking announcements category decreasing slope in three and a half hours only with 10% statistical significance. Inflation (investment) announcement categories point to an increase (decrease) in risk aversion and slope. Index return variable positively affects standardized slope with a 1% statistical significant coefficient. This supports finding of Amin et al. (2004) about volatility spread increasing after stock market increases during the period March 1983 to December 1995.

3.2.1 Asymmetric news effect

Research suggests that investors show asymmetric responses to good and bad news. By separating macroeconomic announcements into good and bad news, we try to assess the asymmetric effects on slope with the following analysis:

Table III

Impact of Macroeconomic Announcement Categories on Slope

Table presents the regression results of $Std\ Slope_t = \alpha + \omega R_t + \sum_k \sum_p \beta_{kt} D_{k,(t-p)} + e_t$ where *Std Slope*$_t$ is slope of implied volatility skew of SPX options calculated as the difference between ATM calls and puts and standardized by daily realized volatility during 2006, R_t is the daily S&P 500 Index return computed on a rolling basis using the last 16 thirty-min time intervals. $D_{k,t}$ is a dummy variable that takes one for the thirty-min interval t that includes a macroeconomic announcement that belongs to category k at time t and zero otherwise. Macroeconomic announcement categories are Employment, Forward-looking, Inflation, Investment and Real Activity. Newey-West correction is used in the regressions. ***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively.

	R_n			**Employment**			**Forward-looking**		
	Coeff.	**t-value**		**Coeff.**	**t-value**		**Coeff.**	**t-value**	
t	17.598	2.204	**	-0.551	-1.443		-0.061	-0.170	
t-1				-0.041	-0.106		-0.422	-1.177	
t-2				0.120	0.314		-0.201	-0.561	
t-3				-0.295	-0.773		-0.247	-0.688	
t-4				0.078	0.202		-0.044	-0.123	
t-5				-0.558	-1.447		0.579	1.637	
t-6				-0.058	-0.150		0.051	0.144	
t-7				0.550	1.428		-0.585	-1.656	*
	Investment			**Inflation**			**Real Activity**		
	Coeff.	**t-value**		**Coeff.**	**t-value**		**Coeff.**	**t-value**	
t	-0.281	-0.658		-0.262	-0.565		0.885	1.675	*
t-1	0.604	1.416		0.700	1.509		-0.165	-0.312	
t-2	-0.188	-0.440		1.030	2.219	**	-0.725	-1.371	
t-3	-0.512	-1.199		-0.454	-0.978		1.005	1.901	*
t-4	-0.198	-0.463		0.556	1.199		0.094	0.177	
t-5	0.608	1.420		-0.469	-1.012		0.731	1.383	
t-6	-0.656	-1.532	**	0.077	0.165		0.425	0.804	
t-7	1.078	2.518		1.365	2.944	***	-1.237	-2.340	**

$Std\ Slope_t = \alpha + \omega R_t + \sum_p \beta_p\ PosDummy_{(t-p)} + \sum_p \delta_p\ NegDummy_{(t-p)} + e_t$ (6) where PosDummy (NegDummy) is a dummy variable that is an aggregation of all good (bad) announcements across all macroeconomic categories. The impact of macroeconomic variables also depends on the surprise created by the announcement. Therefore we test for the impact of good and bad surprises by creating two separate variables. Taking into consideration the multicollinearity problem (news surprises have values at the announcement time while they are zero at other times), we sum standardized surprises across all different categories for good and bad announcements. The following regression estimates the extent to which the surprise component of good and bad announcements impact slope.

$Std\ Slope_t = \alpha + \omega R_t + \sum_p \beta_p\ PosSurp_{(t-p)} + \sum_p \delta_p\ NegSurp_{(t-p)} + e_t$ (7)

We expect that changes in slope of implied volatility skew will vary for good and bad news as investor risk aversion changes with respect to the nature of the surprise. We hypothesize that good surprises will decrease risk aversion and slope, whereas bad news will have an increasing impact on both.

Table IV displays the results of regression in Equations (6) and (7) and show that good and bad news affect the slope of implied volatility skew of S&P 500 Index Options differently. Table presents the results of regressing residuals from the FARIMA modeled standardized slope on one day return and good and bad announcement dummies up to two lags using thirty-min time bars. Good announcement dummy decreases slope by 0.841 at 1% significance level at the

Table IV

Impact of Good and Bad Announcements on Slope

Table presents the results of $Std\ Slope_t = \alpha + \omega R_t + \sum_p \beta_p\ PosDummy_{(t-p)} + \sum_p \delta_p\ NegDummy_{(t-p)} + e_t$ in the first two columns and $Std\ Slope_t = \alpha + \omega R_t + \sum_p \beta_p\ PosSurprise_{(t-p)} + \sum_p \delta_p\ NegSurprise_{(t-p)} + e_t$ in the last two columns. *Std Slope*$_t$ is slope of implied volatility skew of SPX options calculated as the difference between ATM calls and puts and standardized by daily realized volatility during 2006, R_t is the daily S&P 500 Index return computed on a rolling basis using the 16 thirty-min time intervals. *PosDummy*$_t$ (*NegDummy*$_t$) is a dummy variable that is an aggregation of all good (bad) macroeconomic announcements. *PosSurprise*$_t$ (*NegSurprise*$_t$) is sum of standardized surprises for good (bad) announcements Newey-West correction is used in the regressions. ***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively.

	Announcement Dummy			**Announcement Surprise**		
	Coefficient	**t-value**		**Coefficient**	**t-value**	
α	0.011	0.0519		-0.0296	-0.5749	
R_t	17.7335	7.9844	**	17.3929	2.1799	
Good News						
t	-0.4084	0.3171		0.1632	0.7732	
t-1	-0.1435	0.3172		0.048	0.2273	
t-2	-0.8406	0.3173	***	-0.3422	-1.6217	
Bad News						
t	-0.1002	0.3501		-0.2593	-1.2266	
t-1	0.3174	0.3501		0.4547	2.151	**
t-2	0.5546	0.35		0.4829	2.2852	**

second lag. Bad announcement dummy does not affect slope significantly. Table also presents the results of a similar regression on the surprise component of the announcements. Bad surprises increase slope statistically significantly at 5% level at both first and second lags. Good surprises do not seem to affect slope significantly. One day return is positively and statistically significantly related to slope.

3.2.2 VIX and Macroeconomic Announcements

Literature accepts VIX as a good proxy for future index volatility. We aim to analyze the changes of VIX in response to macroeconomic announcements. We first analyze the effects of macroeconomic announcements on the first difference of VIX and then investigate whether there is asymmetric news impact.

Table V presents the results of regressing first difference of VIX on macroeconomic announcement categories controlling for momentum effects. All the regressors except for real activity announcement affect VIX significantly. Employment, forward-looking and inflation announcements are negatively related with changes in VIX, pointing to a resolution of uncertainty with these announcements. The drop in VIX in response to inflation related news is in line with Füss et al. (2011). Unlike Kearney and Lombra (2004), we also find that inflation news affect VIX significantly. The differences in our results may stem from the fact that our analysis is at high frequency. Investment is positively related to VIX at 1% significance level suggesting an increase in uncertainty with this category of announcements.

When we analyze Table VI that shows the effects of good and bad announcements on VIX separately, we see that good news decrease and negative

Table V

Impact of Macroeconomic Announcements on VIX

Table presents the results of $\Delta VIX_t = \alpha + \omega R_t + \sum_k \sum_p \beta_{kp} D_{k,(t-p)} + e_t$ where the dependent variable is the first difference of VIX. R_t is the daily S&P 500 Index return computed on a rolling basis using the last 16 thirty minute time-intervals. $D_{k,t}$ is a dummy variable that takes one for the thirty-minute interval t that includes a macroeconomic announcement that belongs to category k at time t and zero otherwise. Macroeconomic announcement categories are Employment, Forward-looking, Inflation, Investment and Real Activity. Newey-West correction is used in the regressions. ***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively.

	R_t			Employment			Forward-looking		
	Coeff.	**t-value**		**Coeff.**	**t-value**		**Coeff.**	**t-value**	
t	-2.0834	-11.0325	***	-0.0458	-2.9513	***	-0.0403	-2.5142	**
t-1				-0.0462	-2.9603	***	0.0178	1.1148	
t-2				-0.0019	-0.1186		0.0054	0.3401	

	Investment			Inflation			Real Activity		
	Coeff.	**t-value**		**Coeff.**	**t-value**		**Coeff.**	**t-value**	
t	0.0472	2.8888	***	-0.0843	-4.2462	***	0.0097	0.4543	
t-1	0.0176	1.077		0.0083	0.4248		-0.0079	-0.3686	
t-2	-0.0028	-0.1742		-0.0214	-1.0916		0.0207	0.965	

Table VI

Impact of Good and Bad Announcements on VIX

Table presents the results of the regression $\Delta VIX_t = \alpha_t + \omega R_t + \sum_p \beta_p \, PosDummy_{(t-p)} + \sum_p \delta_p \, NegDummy_{(t-p)} + e_t$ and equation 12 where the dependent variable is the first difference of VIX. R_t is the daily S&P 500 Index return computed on a rolling basis using the last 16 thirty-min time intervals. Pos_t (Neg_t) is a dummy variable that is an aggregation of all good (bad) macroeconomic announcements. Macroeconomic announcement categories are Employment, Forward-looking, Inflation, Investment and Real Activity. Newey-West correction is used in the regressions. ***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively.

	Announcement Dummy			Announcement Surprise		
	Coefficient	**t-value**		**Coefficient**	**t-value**	
α	0.0014	1.1084		0.0014	1.1606	
R_t	-2.0098	-10.4614	***	-2.0279	-10.5483	***
Good News						
t	-0.0734	-5.723	***	-0.0341	-3.4335	***
t-1	0.0095	0.7426		-0.0001	-0.0119	
t-2	-0.0032	-0.2486		-0.0063	-0.6368	
Bad News						
t	0.032	2.7207	***	-0.0011	-0.116	
t-1	-0.0193	-1.6398		-0.0143	-1.4956	
t-2	0.0143	1.2175		0.0195	2.0464	**

news increase VIX statistically significantly at 1% level in line with literature about asymmetric news effect on volatility.

3.3 Conclusion

This paper examines the high frequency characteristics of S&P 500 index options' implied volatility skew and VIX. Slope of implied volatility skew is a good proxy for jump risk and investor risk aversion. VIX is a good measure of both market risk and investor 'fear gauge'. In an attempt to explain changes in these parameters proxied by slope and VIX, we examine a broad range of macroeconomic announcements. Results document a statistically significant relation between VIX and macroeconomic announcements even after controlling for liquidity, volatility and momentum effects. The effects of macroeconomic announcements on slope are more gradual compared to responses of VIX. We further categorize announcements into good and bad news to investigate whether there is any asymmetric news effect. We do find evidence that good and bad announcements asymmetrically change slope of implied volatility skew of S&P 500 Index options and VIX.

A clearer comprehension about the factors that affect the slope is important for developing new option pricing models and devising proper hedging and investment strategies. Our results justify why traders shall closely monitor slope to understand how jump risk and risk aversion are evolving during a trading day.

CHAPTER IV

PRESIDENTIAL RHETORIC AND STOCK MARKET VOLATILITY

"News from a reliable source should lead to more portfolio rebalancing than news from an obscure source" (Epstein and Schneider, 2008, p. 197).

4.1 Introduction

The impact of marketplace information on financial markets has been widely researched in finance. For example, recent literature that investigates the effects of macroeconomic news on financial assets' volatility, document that foreign exchange bond and equity market volatility are significantly affected by macroeconomic announcements (Andersen, Bollerslev, Diebold and Vega, 2007). Other recent research associates high-frequency changes in VIX to macroeconomic announcements (Bailey, Zheng, and Zhou, 2012). Some other recent studies are Green (2004), Liu and Wright (2004), Bernanke and Kuttner (2005), Boyd, Jagannathan and Hu (2005), Evans and Lyons (2008) Wongswan (2009), Chen and Gau (2010), Hautsch, Hess and Veredas (2011), Evans (2011) and Elder, Miao and Ramchander (2012). In this paper, we present evidence on an unexplored research area, the effect of United States presidential

rhetoric on stock market volatility. As Presidents are commenting daily, any impact their statements may have on the stock market would be important from both the researcher's and practitioner's perspective. Researchers may wish to include presidential announcements as a control variable when researching market volatility, while investors' portfolio management may benefit from this research.

The causal effect of information and its effect on the stock market has researchers continuing their exploration of this phenomenon. Recent research suggests significant causal effects of financial journalism and aggregate market prices (Dougal, Engelberg, Garcia and Parsons, 2012). The research from 1970-2007 suggested that short term returns on the Dow Jones Industrıal Average (DJIA) can be predicted by focusing on an author from the Wall Street Journal. They did not explore stock market volatility in regard to the WSJ information, but whether the DJIA had excess daily returns in regard to the financial information. During our post-hoc analysis, we also explored whether the impact of the presidential rhetoric would be different per president. Our results agree with this research in that different president's rhetoric had differing impact on market volatility.

Other recent research suggests that political factors do affect the stock market. The research suggests that politics directly affects stock volatility as measured by industry-level factors (international trade exposure, sensitivity to contracts enforcement, and labor intensity) with local and global country-level political variables (elections, autocracy, political risk, and party orientation) (Boutchkova, Doshi, Durnev and Molchanov, 2010). Although there has been much research on stock volatility there is still great disagreement on how to model volatility forecasting attempting to research causal effects (e.g. Bollerslev, Litvinova and Tauchen, 2006; Bekaert and Wu, 2000; Schwert, 1990).

Our research focuses on the president's potential influence on financial markets due to his informal power to give market signals through information in his formal and informal talks. Although the market information nearly always was available prior to the presidential rhetoric, the confirmation, denial or new perspective has an effect on investors as it is considered a reliable source. The president is the only official who is elected by a national constituency, and as such sets the president apart from all other government officials and departments (ex. the Board of Governors of the Federal Reserve) and gives him special authority that no one else has. "The position of the president and the public's reliance on him makes anything the president says important and influential" (Cohen 1995: 96). This is directly related to the president's information asymmetry[6], the increased role of the U.S. government in monitoring and regulating the economy (Kernell 1978), and the president's role as the nation's "chief policymaker" (Brody 1991). The information

[6] Defined by Waterman (2003: 390) as, "the resources of intelligence that the president alone can acquire. Many agencies are involved in collecting information for the presidency (NSA, CIA, Treasury, Commerce). Presidents also use White House organizations (an internal resource) to acquire information (e.g. the Legislative Liason's Office provides the president with information on vote counts in Congress). These sources of information place presidents in a more advantageous bargaining position with other external political actors, both in domestic and foreign affairs."

asymmetry that the president possesses is a function of information being filtered through the massive executive branch bureaucracy. For an item to get on the president's agenda, it must clear many obstacles to get to the White House[7] (Light 1999) which would suggest the importance of each of these items.

Presidents in the United States are responsible for both the economy and foreign policy, which are mutually dependent, as foreign policy affects macroeconomics (Wood, Owens and Durham, 2005). Announcements from the president are not driven by only poor macroeconomic performance, as research suggests presidents talk steadily about the economy when conditions are both good and bad (Wood, 2004). This suggests that volatility is not in response to macroeconomic indicators, but to the information that the President asserts. Presidential signals seem to have an impact as long as they have the authority to act on those signals, act in the short run, and have a measure of credibility in the workplace (Eshbaugh-Soha, 2005).

The assertion that presidential announcements create a market response agrees with previous research that the volatility of prices is directly related to the flow of information to the market (Ross, 1989). Presidential communications could affect stock volatility as the early resolution of uncertainty helps investors to plan (Epstein and Turnball, 1980). Portfolio holders show an aversion to ambiguity (payoff probability occurrence) (Ahn et al., 2010; Bossaerts et al., 2010) and this interaction

[7] Light showed that potential agenda items in the Carter administration typically passed through 13 offices before it reached the president's office, not even including the agencies or department that had to be involved.

between risk and ambiguity are illustrated through stock price volatility from negative political announcements (Bloom, 2009). Although in agreement with the marketplace flow of information affecting the stock market, contrary research suggests that ambiguity aversion correlates with portfolio inertia and can explain sudden market freezes (Easley and O'Hara, 2010). When political news is negative, investors maintain investment inertia as they can find risky stock allocations to hedge against such ambiguous news (Illeditsch, 2011).

Financial asset risk and return is influenced by political uncertainty and there is a negative association between financial asset valuations and the level of economic uncertainty (Sy and Al Zaman, 2011; Ozoguz, 2009). The uncertain information hypothesis, based on the core assumptions of the efficient market hypothesis, suggests that investors are rational and are able to identify whether news is positive/negative but not able to ascertain the true impact (Brown, Harlow and Tinic, 1988). As an example, research suggests that the prior two weeks before a political election there is an increase in stock prices (Pantzalis et al., 2000). Other research focuses on the uncertainty of the election and finds that stock markets are affected negatively if there is high uncertainty (Goodell and Body, 2012). Recent research provides support for the political uncertainty hypothesis (which presumes election results give information in regard to potential macroeconomic policies affecting business and stock prices) thus implying the importance of information of political nature in regard to public policy and stock markets (Goodell and Vahamaa, 2013).

Examples of politics affecting stock markets have been illustrated from both theoretical and empirical evidence (Fowler, 2006). For example, the volatility index of the Chicago Board Option exchange increased by 17% when the U.S. House of Representatives voted against the Federal Reserve bailout on September 29, 2008. Some research has examined stock market volatility and the political environment (e.g. Fuss and Bechtel, 2008; Leblang and Mukherjee 2005; Bialowski, Gottschalk and Wisniewski, 2008), but none has examined presidential announcements and volatility. As it has been noted that the President often delivers information regularly, the impact on the stock market is of great interest to researchers.

Research into policy change announcements suggest that stock prices fall when a policy change is announced through general equilibrium modelling (Pastor and Veronesi, 2012). Political news can be classified as positive (favorable) and negative (unfavorable) with favorable news decreasing uncertainty and unfavorable news increasing uncertainty. According to Beaulieu, Cosset and Essaddam (2005), favorable news decreases stock return volatility and unfavorable political news increases stock return volatility. Positive political announcements have small effects while negative announcements of policy changes will have larger effects due to the surprise element (Pastor and Veronesi, 2012). Recent research proposing a new model of information suggests that investors discount good news and react to bad news with asymmetric responses skewing the distribution of observed returns: uncertain quality of the news generates negative skewness while signals of known quality generate positive skewness (Epstein and Schneider, 2008). Other recent research examining how information affects stock volatility modelled news as good or bad against stock volatility (Chen and Ghysels, 2010). The results of their research suggest good news reduces the next day's volatility, very good news and bad news increases next day volatility.

Our research categorizes presidential announcements as negative, positive and neutral utilizing tailored-made keyword filtering software applications followed by double blind researcher evaluations to classify announcement type. Our data is collected from 51,500 pages of Public Papers of the President of the United States covering the presidencies of Reagan, Bush and Clinton. The effect of the presidential signals on the volatility of the S&P 500 Index is tested using GARCH modelling and controlling for macroeconomic announcement dates and the recessions for the period of 1981 to 1999. Our results show that both positive and negative presidential signals have a statistically significant increasing effect on stock market volatility. The effect of negative presidential rhetoric is more profound compared to positive signals.

The organization of the paper is as follows. Section one describes the testable hypothesis. Section two explains the data collection process. Section three discusses presidential signal categorization methodology and the choice of control variables. Section four presents empirical tests and results. Section five concludes.

4.2 Testable Hypotheses

Our primary purpose of this study is to discuss the relationship between presidential rhetoric and its effect on the stock market. Marketplace information has most likely already been made available to investors prior to the presidential rhetoric, but the president then confirms, denies, or puts their own twist on the information. Past research suggests that information can be positive, negative or neutral. We test the following hypothesis in regard to presidential rhetoric and the stock market:

H1: Negative rhetoric from the president will increase volatility in S&P 500 Composite Index.

H2: Positive rhetoric from the president will increase volatility in S&P 500 Composite Index, but less than negative rhetoric.

H3: Neutral rhetoric from the president will decrease volatility in S&P 500 Composite Index.

The rationale for our hypotheses, in summary, is that the president is very influential and the first time he discusses marketplace information (the economy, inflation/interest rates, or the deficit) his input will cause investors to rebalance their portfolio. As investors are risk averse, negative news should have a greater impact than positive news. Neutral news (those comments which are made a second time (or third time, or fourth, etc.) or are of nothing that is of importance to the USA) will confirm to investors that no new information is forthcoming.

Our research continues the stream of research on how investors react to public information. For example, one recent study explores public information and its impact on the volume of trades of stocks and options (Cao and Ou-Yang, 2008). The research suggests that stock trading and options trading react differently to public information. Trading volumes of stock fluctuate based upon individual idiosyncratic views differing about a stock's pay-off due to public information. As each investor sees the public information from differing viewpoints as well as a constant absolute risk aversion, stock purchases/sales will be different per investor as the ultimate stock pay-off will be viewed differently. Investors interpret public information differently as investors have heterogeneous views over the same information (Kandel and Pearson, 1995).

Research does suggest that the trading volume of stocks reacts to current public information. The trading volume reaction occurs based upon four components; level of optimism/pessimism of public signal, its precision in regard to future periods, differences of opinion about the current information, and the differences of opinion of all past signals (Daniel, Hirshleifer, and Subrahmanyam, 1998, Hong and Stein, 2003). Our research further explores a key informational element, that of presidential rhetoric and the investors' reactions to his statements.

4.3 Methodology

4.3.1 Data

In this study, we are exploring whether investors respond to president's signals. Signals are pieces of information communicated to individuals – either intended or unintended – that allow individuals to make decisions on a variety of issues (Eshbaugh-Soha, 2006). When the president sends signals to the market, signals are available to all participants in the market because the president is monitored by 24/7 cable news. We are analyzing what the president says formally, and informally, and how that message affects stock market volatility which is an important variable used in many financial decisions. We hypothesize that when presidents make **new** positive or negative comments about the economy, that signal would create a short-term market response. The response is expected to be more profound following the negative signals from the president about the state of the economy. To the best of our knowledge, there has been no empirical work performed on the impact of the president's rhetoric on financial market volatility. There has been considerable work on presidential rhetoric (Tulis, 1987), and a large body of work by Wood (2002; 2004; 2007) and Wood, et al (2005) on the president's rhetorical impact on the economy, but the impact of the president's rhetoric on financial market volatility has been left unattended.

4.3.1.1 Presidential Signals Data

In order to properly collect, code, and analyze presidential signals as they relate to market responsiveness, data is used from two primary sources (Public Papers and Datastream) and a software application was created uniquely for this project. For presidential signals, an electronic file of the *Public Papers of the President of the United States*[8] provides the most thorough and comprehensive information including press conferences, Q & A sessions with reporters, radio addresses, addresses to joint sessions of Congress, addresses to the nation, and announcements of economic programs of any president. In other words, every time the president says something about the economy that has been recorded by the *Public Papers* it will be included in

[8] An electronic file containing the Public Papers of the Presidents was generously provided by B. Dan Wood from his research on presidential rhetoric and the economy (Wood, 2004; Wood, et al, 2005; Wood, 2007). Dr. Wood obtained the file from the Western Standard Publishing Company (Wood, 2007) that contained the Papers through 1999, where our analysis ends.

our analysis. The study covers 1981 to 1999. All prepared and unprepared statements, proclamations, etc., that Presidents Reagan, Bush, and Clinton made about the economy, whether they are positive, negative, neutral, intended or unintended, verbal or written, are coded.

Presidents often repeat signals and rehash speeches about the economy, education, and social security, to name a few issues. The research design assumes that if institutional investors pay attention to what the president says, then they pay attention to the first signal of new information the president makes about the economy, not the 2^{nd}, 3^{rd}, 4^{th}, etc., because they will have made their buying or selling decision on the first signal, not the ones the president repeats ad nausea throughout the day. This is particularly true for re-election years when the president is trying to talk up his handling of the economy. He may say something positive or negative at the beginning of the day, or at the beginning of the campaign. That signal may create a market response, but the subsequent comments are assumed to be not significant and thus are coded as *Neutral*.

4.3.1.2 Stock Market Data

The second primary source of data gathering and analysis is the daily closing values of Standard & Poor's 500 (S&P 500) Index downloaded from Datastream. S&P 500 Index is a weighted combination of 500 firms chosen based on their market capitalizations and represents the large cap firms. Investors use this index to track the broad domestic economy.

4.3.2 Presidential Signal Categorization / Inter-rater Reliability

The software application designed uniquely for this project allows us to do keyword searches, as well as collate and rate the keywords. The first tool, the RTF (rich-text format) document parser, reads through (parses) extremely large RTFs Public Papers of the President of the United States, and isolates publication year, publication date, the publication title (President's Remarks at a News Conference, for example) and the paragraph text under that particular title. President Reagan's page count from 1981 to 1988 is 18,120, President Bush's page count from 1989 to 1992 is 10,512, and President Clinton's page count from 1989 to 1999 is 22,906. The second tool, the natural text search engine of Oracle database technology, provides a visual front-end on the primary database table structure. The basic keyword search operation allows the user to search approximately 51,500 pages for the keywords that are of interest. Documents that match are returned into a separate tree view control. After parsing and categorization of texts, separately two graduate students examine each paragraph and identify when the president used the keywords positively, negatively, neutrally, or not at all (we will discuss Interrater reliability next). If the president does not signal new positive or negative information but merely restates his earlier news then that signal is coded as neutral. The details for categorization is given in the following section.

As Laver et al. 2003 note, the use of computer-aided analysis offers a dramatic increase in the amount of text that can be analyzed and automates the tediousness of human coding. However, it is not a substitute for a good research design and computer-aided analysis does not do away with extensive human input. For example, just looking at a sentence that contains the keyword *Economy*, may not capture that the President is talking about Japan's economy and not the United States'. Moreover, computer programs fail to pick up nuance in a president's remarks and cannot handle words that have more than one meaning, phrases, or idioms and thus human coding is needed (Weber, 1990).

After two raters finish coding all keyword signals, an analysis of inter-rater agreement[9] is to be determined to establish reliability. Based on guidelines provided by Lombard, et al. (2002) for calculating and reporting inter-rater agreement, the following steps are taken: First the measure of inter-rater agreement is determined, using the proportion of percentage agreement, defined as:

$$p = \frac{N_a}{N_a + N_d} \qquad (1)$$

Where N_a is the number of agreements and N_d is the number of disagreements. The proportion of percentage of agreement is used because it is the most widely used, intuitively appealing, simple to calculate, and, "…the foundation upon which…measures of agreement are constructed" (Tinsley and Weiss, 2000: 112).

[9] Inter-rater agreement is, "…the extent to which the different [raters] tend to assign exactly the same rating to each object" (Tinsley and Weiss, 2000: 98).

Second, a minimum acceptable level of reliability is chosen as 90% or greater, because that level of reliability is nearly always acceptable for proportion of percentage agreement (Lombard et al, 2002). Third, a pilot test is performed of 30 signals selected randomly by year, by month and then by keyword. The first positive or negative signal in the random month, the random year, and by the random keyword is selected as the starting point. This is done, so that the raters randomly select a neutral comment that may have appeared positive, but would not have been coded positive, because the president signaled that same comment earlier in the week. A minimum of 30 signals after the starting point are analyzed chronologically. After that selection is analyzed, another year, another month, and another keyword is selected at random, and so forth. Reliability for the 30 signals is 100% for the pilot test. Fourth, since the pilot test indicates that reliability levels will be adequate, another sample of the signals is performed. According to Lombard et al. (2002), the larger sample should not be fewer than 50 and it is not necessary to examine more than 300. Based on the pilot test, 400 signals are examined.

In Table I, agreements between raters are displayed along the diagonal cells. For example, on October 22, 1998, both raters identify the signal as *Positive*. That agreement is placed in the upper left cell, Row 1, Column 1. Conversely, the raters did not agree on May 27, 1999. Rater 1 coded the signal as *Positive* and Rater 2 coded the signal as *Neutral*. That disagreement is inserted in Column 1, Row 3. The agreements between raters are located on each diagonal cell. Disagreements between the raters are be placed in one of the off-diagonal cells.

Table I

Inter-rater Agreement

The agreements between Rater 1 and Rater 2 are located on each diagonal cell. Disagreements between raters are located in the off-diagonal cells. According to Lombard et al (2002) an acceptable level of reliability is 90% or greater. Aggregating the diagonal cells of agreement, the raters agreed on 372 out of 400 signals, or 93%, exceeding Lombard's (2002) level of reliability.

Rater One

		P	**N**	**NTR**	**NV**		**Total**
	P	**37**	17	8	0		62
	N	0	**13**	0	0		13
Rater Two	**NTR**	2	1	**303**	0		306
	NV	0	0	0	**19**		19
						372	
	Total	39	31	311	19		**400**

The row and column totals are computed and then the total number of agreements are calculated, adding diagonally and then dividing the total number of agreements by the total number of signals selected. In this case, 372 agreements, agreement divided by 400 signals, equal the proportion of percentage agreement again, or 93%. The 93% agreement passes the 90% threshold that was established beforehand. However, as a more robust measure, Cohen's kappa (κ) is also performed, indicating the proportion of agreements between two raters, adjusting for agreements occurring by *chance* (Tinsley and Brown, 2000), and is calculated as:

$$k = \frac{P_a - P_c}{N - P_c} \qquad (2)$$

Where, N is the total number of signals in the sample, P_a equals the proportion of ratings in which two raters agree, and P_c equals the proportion of agreement between raters that occurred by chance. The expected frequency of chance agreements can be calculated as:

$$P_c = \sum_{1=j}^{k} P_{ef} \qquad (3)$$

Where, P_{ef} equals the product of the marginal proportions. For the data in Table II, the classification by the two raters is presented. Cohen's Kappa, or κ, can vary from 1.00 (perfect agreement) to -1.00 (perfect chance). A value of zero is equal to agreement that could be expected by chance and any value that is negative of the observed agreement is less than the chance agreement (Tinsley and Weiss, 2000).

Referring to Table II, the expected frequencies for the number of agreements that would have been generated by chance are calculated along the diagonal rows, by multiplying the row total times the column total and then dividing by the overall total. For example, the *Positive* row total of 62 times the *Positive* column total of 39 divided by the total number of signals in the sample, 400, equals 6.05. The result is the expected frequency. The sum of these expected frequencies across the diagonal is used to calculate κ. The percentage agreement between the two coders, adjusting for chance agreements, equals 79.29%. Landis and Koch (1977: 165) provide a table for interpreting κ values, and those values are reproduced in Table III. The 79.29% agreement between coders suggest that inter-rater agreement is "substantial".

4.3.3 Presidential Signal Categories

Using the software application, that tagged keywords and separated out paragraphs with those keywords for easy identification, signals are identified as *Positive, Negative, Neutral,* or *No Value* (Table IV) by examining a list of keywords, *Economy, Deficit, Inflation, and Interest Rate* (Table V)[10]. Positive signals are defined as optimistic economic news, initiatives, proclamations, etc. that the market would react favorably signaled during a given day by the president for the first time. *Negative* signals are defined as new negative economic news, proclamations, sanctions, etc. that the market would react unfavorably, signaled during a given day by the president for the first time. Two examples from Table IV illustrate positive and negative signals. On July 5th, 1983, President Reagan gave a memo on the import relief in steel industry. Not only is this information positive, but it was information confirmed by the president for the first time.

[10] Besides the Economy, Deficit, Inflation, and Interest Rates keywords mentioned earlier, other keywords that were believed to be significant because of their impacts on financial markets, were quickly dropped from the analysis. Like Wood's footnote (2004:576) other keywords were considered, such as "weakness", "economic growth", "economic conditions", "unemployment", "earnings", "corporate earnings", "commodities" "housing market", "oil", and "unemployment", but these were dropped because those keywords were used too infrequently, not at all, or were quickly determined as not relevant to the analysis. For example, the phrase "housing market" was uttered by President Reagan only nine times in eight years, President Bush did it 16 times in four years, particularly in 1992 when he was running for re-election and trying to convince the American people that his economic programs were working. Also, "bonds" was dropped because so many of the isolated words referred to bonds of friendship; "debt" was dropped because so many were "debts of gratitude", "debt that can't be repaid"; "bond market" – used too infrequently to make a difference, "corporate earnings" and "strength/weakness of the dollar"– not used by all presidents, and "earnings" - because there were very few references to financial earnings, but rather as personal earnings in terms of wages.

Table II

Cohen's Kappa

κ can vary from 1.00 (perfect agreement) to -1.00 (perfect chance). A value of zero is equal to agreement expected by chance and any value that is negative of the observed agreement is less than the chance agreement. The expected frequencies for the number of agreements that would have been generated by chance are calculated along the diagonal rows from Table II, by multiplying the row total times the column total and then dividing by the overall total. For example, in Table II, the P row total of 62 times the P column total of 39 divided by the total number of signals in the sample, 400, equals 6.05. The result is the expected frequency. The sum of these expected frequencies across the diagonal is used to calculate κ.

Rater One

Rater Two

	P	**N**	**NTR**	**NV**	
P	6.05	1	1	0	
N	0	1.01	0	0	
NTR	8	0	237.92	0	
NV	0	0	0	0.90	
				$\boldsymbol{P_{ef}}$	**264.87**

$$k = \frac{P_a - P_c}{N - P_c} = \frac{372 - 264.87}{400 - 264.87} = \frac{107.13}{135.13} = .7929$$

Table III

Agreement Strength for Signaling Data

Kappa Statistic	**Strength of Agreement**
<0.00	Poor
0.00 - 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Nearly Perfect

Frequencies provided by Landis and Koch (1977).

Table IV

Example Paragraphs of Positive, Negative, Neutral and No Value Signals from *Public Papers* of *President Reagan* Using Software Application

Each example reflects the application's ability to search and find positive signals from President Reagan, for our keywords of interest, *Economy*, *Deficit*, *Inflation,* and *Interest Rates*

Positive

07/05/83: Pursuant to Section 202(b) (1) of the Trade Act of 1974 (P.L. 93 - 618), I have determined the action I will take with respect to the report of the U.S. International Trade Commission (USITC), transmitted to me on May 6, concerning the results of its investigation, which was requested at my direction, on the merits of providing import relief to the specialty steel industry. I have determined that the granting of relief is consistent with our national economic interest and is necessitated by the pervasive nature of unfair trading practices in specialty steel.

I will, therefore, proclaim import relief but in a modified form and duration from that recommended by the USITC. I will impose relief for four years rather than three, as recommended by the USITC, to provide time for the industry to complete important investment projects, improve productivity, and regain profitability. I have decided to provide relief in a form consistent with my belief in minimal government interference in the marketplace, and which will facilitate the orderly adjustment of the industry while recognizing the substantial differences in the competitive conditions of the various segments of the industry.

Negative

3/19/93: This [health care crisis] is a devastating blow to our efforts to reduce the *deficit.* If you want us to bring the budget into balance, you must insist that after we pass this budget, we move on to find a way to bring health costs in line with inflation and provide a basic package of health care to all of our people. By the end of the decade we'll be spending 20 percent of every dollar, 20 cents on the dollar, on health care. And none of our competitors will be over a dime, and we will be in a serious hole in terms of trying to be competitive. We also cannot balance the budget.

Neutral

10/6/99: You look at what happens to these countries that try to hide their money; people still get it out. *Interest rates* are set in a global economy. If we get America out of debt, it means that all the Americans can borrow more cheaply. If the Government is out of debt, it means lower *interest rates* for businesses in this country, for home loans, for car loans, for college loans. It means more jobs and higher incomes.

No Value

12/17/96: During the past 12 months, [the NATO-led Implementation Force] separated and ensured the demobilization of former warring factions. It provided the secure conditions in which democratic elections could be held and the reconstruction of Bosnia's shattered economy could begin.

President Clinton's signal on March 13, 1993 is clearly negative, "This [health care crisis] is a devastating blow to our efforts to reduce the *deficit.*" Since presidential signals are coded chronologically, this is the first time that President Clinton talked about an issue being devastating to the deficit, which at the time, the deficit was a major issue for the president. Just the month previous, he had to renege on his promise of not taxing the middle class.

Information that the president signals to the market for the first time is of interest in this study. The president may say, "I'm very encouraged by some recent economic news that will come out later today." That is information that the president signals for the first time. Investors might have speculated that there was good news the previous day or the previous week, but it was not confirmed until the president signaled it, as in the above example. Each additional mention of his optimism about the economic news he signaled earlier in the day, either later that day or over the next few days, is now considered old information. Those second and third signals are coded as *Neutral*.

To be true to the concept of examining the president's signals as an institutional investor would do, each signal has to be examined and *coded chronologically*, to discount those signals that the president repeats in stump speeches or on the campaign trail. The Federal Reserve Chairman's remarks typically create volatility (Bernanke and Kuttner, 2005), but the Chairman only speaks in public a few times a year. The president, on the other hand, speaks in public all the time, so a comment that he might make over and over again may not have the same impact as does the Federal Reserve Chairman's rare statements. For example, in March 1982, President Reagan made over 80 comments about the economy on 21 separate occasions, in just one month. Therefore, while the president sends 5,764 signals to the market over the 18 year time period, the analysis produces 370 *positive* signals and 199 *negative* signals, against 4686 signals that are coded as *neutral* and 509 signals that are coded as *no value*. From February 15, 1993 - when President Clinton announced that he was going to renege on his promise of a middle class tax cut and turn to the wealthiest Americans for more money to reduce the deficit - to August 10, 1993 when his deficit reduction package was passed, President Clinton gave the same speech, or some variant of it for six months – mentioning the deficit 1,075 times[11] (he would only mention the deficit 1,947 more times in the next 7.5 years) and how hard he was working on the problem.

Presidents often repeat signals and rehash speeches about the economy, education, and social security, to name a few issues. The research design assumes that if institutional investors pay attention to what the president says, then they pay attention to the first signal of new information the president makes about the economy, and less to the 2nd, 3rd, 4th, etc., because they will have made big chunk of their buying or selling decisions on the first signal, and less so for the ones the

[11] These numbers reflect every time the president uttered the word *Deficit.*

Table V

Keyword Descriptions

Keyword	Description
Economy	The total wealth and resources of the United States in terms of the production and consumption of goods and services
Deficit	When government spending exceeds the receipts (tax revenue) it receives in a given year. The total accumulation of these deficits is the national debt. Governments finance deficits through the bond market
Inflation	An increase in the overall prices of goods and services in an economy and the inflation rate is the percentage change in the Consumer Price Index – a measure of the overall cost of the goods and services bought by a typical consumer - from one period to the next, measured monthly.
Interest Rates	The supply of money into the system is under the partial control of the Federal Reserve System as it manipulates the federal funds rate through the open market operations. As interest rates increase, economic actors should borrow, consume, and invest less; as they decrease, economic actors should borrow, consume, and invest more.

All definitions taken from (Mankiw, 2007) president repeats ad nausea throughout the day. This is particularly true for re-election years when the president is trying to talk up his handling of the economy. He may say something positive or negative at the beginning of the day, or at the beginning of the campaign. That signal may create a market response, but the subsequent comments are assumed to be less significant and thus are coded as *Neutral*.

For example, President Bush talked about how the economy was "starting to move" on May 19, 1992. President Bush repeated this phrase on May 20, 21, 27, and 28. This methodology cuts down on the number of positive and negative N's in the study, because if every time the president says "the economy is improving" was included in the analysis, this study would have an exponentially larger number of N's. However, through the lens of an institutional investor, those actors that create the market volatility, the number of positive and negative comments actually diminish, because the president's "starting to move" signal has already been factored into other information that they have already received. When the president repeats the signal, this does not add to his decision-making process.

The research presented here assumes that when certain words are analyzed out of context of the U.S. financial markets, there will be no effect and will be coded as a having *No Value*. For example, President Reagan mentions on November 11, 1983 that the Japanese "*economy*" will soon pass the Soviet Union's to become the second largest on the planet, that signal is coded as having *No Value*. Also, if the president is

Table VI

Average Number of Signals per Year

This table presents summary statistics of the average number of times President Reagan, Bush, and Clinton signaled to the market each year, using keywords *Deficit, Economy, Inflation, and Interest Rates*, from January 1981 to December 1999

President	Deficit	Economy	Inf&Int Rates
Reagan	61	115.5	108.25
Bush	60.25	134.25	55.25
Clinton	94.86	152.43	107.86

referencing a historical fact[12], that is coded that as *No Value* as well. Descriptive statistics on presidential signals are in Table VI and VII.

4.3.4 Controlling for Macroeconomic Announcements

Presidential signals are categorized as new if the president is talking about them for the first time. However, investors are also following official macroeconomic announcements and these announcement releases may coincide with the presidential signals that we are analyzing. In this regard, we need to control for a significant number of announcements in our study including Consumer Price Index (CPI), Producer Price Index (PPI), Industrial Production and Capacity Utilization (IPCU), New Residential Construction, Productivity and Costs, Gross Domestic Product

[12] For example, President George H.W. Bush, during his re-election campaign of 1992, mentioned over 50 times that during the Carter administration, inflation was at 15% and interest rates were at 21%.

Table VII

Number of Positive and Negative Signals to the Market

This table presents summary statistics of the number of times President Reagan, Bush, and Clinton sent a positive and negative signal to the market, using keywords *Deficit, Economy, Inflation, and Interest Rates*, from January 1981 to December 1999.

President	**Deficit**			**Economy**			**Inf&Int Rates**		
	Pos	Neg	Ntrl	Pos	Neg	Ntrl	Pos	Neg	Ntrl
Reagan	36	14	422	85	38	658	30	15	741
Bush	10	8	196	70	52	340	20	13	139
Clinton	42	7	599	53	53	887	24	8	704

(GDP), Employment Situation (Unemp), Personal Income and Outlays (PI) and Federal Open Market Committee (FOMC) meeting dates. These are the major announcements that are employed in the literature investigating effects of macroeconomic news on the financial markets. The data for macroeconomic announcements is collected from the website of Federal Reserve Bank of St. Louis. FOMC meeting dates are kindly provided by Gurkaynak et al. (2005). Table VIII reports release timing, the institution that makes the release and the frequency for the macroeconomic announcements that we include as controls. We control for the announcement effects by employing a dummy variable which takes one on the day of an announcement and zero otherwise.

There is also evidence that news effects differ across business cycles. Investors may react to the same set of news differently in good and bad times (Blanchard , 1981; McQueen and Roley,1993). For example Andersen, Bollerslev, Diebold and Vega (2007) find that positive PPI and CPI shocks have significant effects on stock markets during expansion while the same inflationary shocks do not have a significant effect on stock markets during recession. In this respect, investors may also react differently to presidential signals during expansions and recessions. Although our macroeconomic announcement day dummies may interact with the business cycle timing, we control for the business cycle effect with employing dummies for the recessions. The data for the chronology of business cycles are obtained from the website of the National Bureau of Economic Research (NBER). We have only three recessions in our sample period. The first one starts January 1980 and lasts for six months. The second one starts July 1981 and lasts for 16 months. The final recession starts July 1990 and lasts eight months.

4.4 Empirical Tests

This study explores how the president's rhetorical signals influence the stock market volatility of S&P 500 Composite Index. In order to capture the time varying nature of the conditional variance of returns of the indices, we use Generalized Autoregressive Conditional Heteroscedasticity (GARCH) modeling, proposed by Bollerslev(1986)[13]. Widely used GARCH processes use past unpredictable parts of returns, generally referred to as shocks, to predict the future volatility. A univariate GARCH (p,q) model can be written as:

[13] There are newer models like GARCH-X (Han and Kristensen, 2014).

$$R_t = \mu + \varepsilon_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \qquad (4)$$

$$\overline{\omega} = \frac{\omega}{1 - \alpha - \beta}$$

where R_t is the return on an asset at time t , ε_t is the forecast error or shock, σ_t is the conditional variance of R_t, ω, α_i and β_j are the parameters, p and q refer to the number of lags of shocks and conditional variances respectively. $\overline{\omega}$ is the constant long run

Table VIII

Control Variables

This table reports release timing, the institution that makes the release and the frequency for the macroeconomic announcements.

Announcement	**Source**	**Frequency**	**Timing**
Real Activity			
Industrial Production	FRB	Monthly	On or around the 16th of the month
Capacity Utilization	FRB	Monthly	On or around the 16th of the month
Employment Situation	BLS	Monthly	The first Friday of the month
Personal Income and Outlays	BEA	Monthly	4-5 weeks after month\'s end
Productivity and Costs	BLS	Quarterly	Apprx. 5 weeks after previous quarter\'s end
GDP	BEA	Quarterly	Three months after quarter ends
Prices			
Consumer Price Index(CPI)	BLS	Monthly	Last Tuesday of the month
Producer Price Index(PPI)	BLS	Monthly	Second or third week of the month
Forward Looking			
New Residential Construction	CB	Monthly	On or around the 17th of the month
FOMC Meeting Minutes	FRB	Every six-week	
Recession	**Start**	**Duration**	
	January1980	6 Months	
	July 1981	16 Months	
	July 1990	8 Months	

Abbreviations are Federal Reserve Board (FRB), Bureau of Labor and Statistics (BLS), Bureau of Economic Analysis(BEA) and U.S. Census Bureau(CB).

volatility of the return process.

GARCH models have many appealing characteristics. They manage to capture the volatility clustering phenomenon, which is an important empirical characteristic of asset distributions. Moreover the return distribution that evolves from a GARCH process has fatter tails than a normal distribution, which is again documented by many researchers starting with Fama (1965). They also have long run forecasting abilities, by capturing the concept of mean reversion with the help of a constant intercept term.

Our analysis includes the following models. Model 1 employs dummies as exogenous variables in the variance equation of GARCH (1, 1) model for the *Positive* and *Neutral* signals that the president sends to the market; Model 2 includes dummies in the variance equation for the *Negative* and *Neutral* signals that the president sends to the market. In these two models positive and negative signal categories aggregate signals over each category. Model 3 employs separate dummies for positive and negative presidential signals on economy, deficit and inflation/interest rates. All three models include control variable dummies in the conditional variance of Equation 5. We also employ AR (1) term in the return series of Equation 5 to account for the empirically documented non-synchronous trading effects. Business cycles are represented by a binary variable with days in recession period taking one. We report only the dummy variables with statistically significant t-values.

$$R_t = \mu + R_{t-1} + \varepsilon_t \tag{5}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{m=1}^{9} \theta_m Signal_m + \sum_{m=1}^{9} \gamma_m MacroDummy_m + \delta Recession$$

Results are summarized in Table IX. As suggested by a highly significant GARCH coefficient and sum of ARCH and GARCH coefficients that is close to unity, all of our models are covariance stationary and the conditional variance exhibits a high level of persistence. The Ljung-Box test statistics based on squared residuals indicates that there are no serial correlations. We report coefficients and robust t-statistics calculated with the Bollerslev-Wooldridge (1992) method.

President's negative signals have an increasing effect on the volatility of the S&P 500 Index. Positive signals also increase volatility in the market as with any other information arrival but the effect is substantially less compared to the impact of negative news. This finding is in line with the well-known leverage effect in the literature and the arguments of Epstein and Schneider (2008). President's Neutral statements, or reinforcements of prior information, decrease market volatility. These findings are intuitive considering that the president has the advantage of information asymmetry and when sending a signal to the markets, he does not have to negotiate with other political actors, like Congress, to be effective. Therefore investors change their positioning with respect to the presidential signals.

In line with prior literature, we find that macroeconomic announcements such as Consumer Price Index, Producer Price Index, Industrial Production/Capacity Utilization, Gross Domestic Product (GDP), Employment Situation, and Personal Income and Outlays create short term fluctuations in the markets. As a robustness

We performed analysis on the president's positive, negative and neutral statements in regard to the separate specific categories of economy, deficit and inflation/interest rate check we conducted the regressions removing days when there is both a positive and negative signal and the results were similar.

4.5 Post-hoc Analysis

We performed analysis on the president's positive, negative and neutral statements in regard to the separate specific categories of economy, deficit and inflation/interest rate on the volatility of the S&P 500 Index separately (see Tables 9 and 10). Investors seem to respond predominantly to the signals on the state of the economy. Volatility increases the most when presidential rhetoric signals negative information about economy. When the president mentions already signaled news (coded as "neutral") on economy, volatility decreases. When he repeatedly signals statements on inflation and interest (coded as "neutral"), volatility of S&P 500 increases. These effects are significant after controlling for the macroeconomic announcements (Table IX: Model III) and after not controlling for the macroeconomic announcements (Table X).

Table IX

GARCH (1, 1) Estimates for S&P 500 Index Returns on Presidential Signals and Controls

This table presents results for the estimation of following GARCH models.

$$R_t = \mu + R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{m=1}^{9} \theta_m \, Signal_m + \sum_{m=1}^{9} \gamma_m \, MacroDummy_m + \delta Recession$$

Model 1 includes only the Positive and Neutral signals that the president sends to investors; Model 2 includes only the Negative and Neutral signals that the president sends to the market; Model 3 includes all the specific presidential signals. Macroeconomic announcements and business cycles enter the conditional variance equation as control dummies. We report only the variables with statistically significant t-values. Full tables are available upon request. The return series is the S&P 500 Composite Index daily returns. Sample period is 1981 to 1999. We report the coefficients and robust t- statistics calculated with the Bollerslev-Wooldridge (1992) method.

	Model I		**Model II**		**Model III**	
	Coefficient	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Constant in Mean	0.0639	5.535	0.0655	5.708	0.0643	5.607
AR(1)	0.0524	3.114	0.0519	3.081	0.0526	3.114
Constant in Var.	0.0204	3.825	0.0197	3.776	0.0175	3.597
ARCH(1)	0.0791	32.022	0.0797	32.271	0.0794	32.485
GARCH(1)	0.9049	190.878	0.9046	193.942	0.9046	194.27
All Positive	0.0287	2.038				
All Negative			0.0703	3.489		
All Neutral	-0.0140	-2.919	-0.0125	-2.871		
Economy Neutral					-0.0186	-3.036
Economy Negative					0.0821	3.502
Inf/Int Neutral					0.0153	2.252
Controls						
Unemp	0.1190	4.498	0.1143	4.382	0.1223	4.594
PPI	0.1153	4.16	0.0922	2.876	0.0902	2.733
GDP	-0.1312	-4.158	-0.1281	-4.097	-0.1263	-4.158
Prod. Costs	-0.0988	-3.557	-0.0874	-3.257	-0.0994	-3.477
Recession	0.0154	3.031	0.0138	2.771	0.0137	2.7

Table X

Post-Hoc Analysis-Without Macro-Economic Controls

This table presents results for the estimation of following GARCH models.

$$R_t = \mu + R_{t-1} + \varepsilon_t$$
$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{m=1}^{9} \theta_m \, Signal_m$$

The return series is the S&P 500 Composite Index daily returns. Sample period is 1981 to 1999. We report the coefficients and robust t- statistics calculated with the Bollerslev-Wooldridge (1992) method.

	Neutral		Negative		Positive	
	Coefficient	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Economy	-0.0143	-2.087	0.1220	6.087	-0.0221	-1.089
Infl./Interest	0.0143	2.058	0.0179	0.486	0.0185	0.570
Deficit	-0.0120	-1.482	0.0026	0.047	-0.0079	-0.281

4.6 Conclusion

Financial markets are influenced by marketplace information and our research explored presidential rhetoric in regard to financial market volatility. We investigate this hypothesis by studying over 51,000 pages of presidential announcements over nearly 20 years of presidential signals about the deficit, economy and inflation/interest rates that were classified as positive, negative or neutral and their effect on the S&P 500 Composite Index volatility. Our research utilized GARCH modeling and suggest that negative signals increase volatility, positive signals also increase volatility but on a substantially less scale, and neutral statements slightly decrease market volatility. Ambiguity-averse investors are more likely to react to negative signals more strongly than positive signals in line with previous research (Epstein and Schneider, 2008).

Presidential rhetoric is an important research area as presidents are continuously making announcements and research suggests that news from a reliable source will lead to more portfolio rebalancing. Illeditsch (2011) argues that when investors receive information that is difficult to process, investors' desire to hedge ambiguity leads to excess volatility. We argue that presidential rhetoric is an important and reliable source of information and affects market place volatility with negative and positive presidential signals leading to higher volatility. The result that a neutral signal from the president reduces market volatility would suggest that this type of information reassures investors that there is nothing to add to their already acquired market information.

Our empirical findings indicate that information from a reliable source, in this case the president, does affect market volatility. Our research suggests that institutions and other financial participants involved in the stock market should take heed of presidential announcements and the resulting market volatility. Financial participants have access to a large amount of data and information daily and presidential announcements confirm, heighten or contradict their privately held information with resultant heightened or lessoned volatility. As the reputation of the president is of importance, the quality of presidential rhetoric should be very high. As there are many stages whereby different information is expunged on its way to the president, only the key information is elicited by the president to the populace, thus enhancing its value.

CHAPTER V

CONCLUSION

This thesis aims to determine the factors that affect variability in slope of implied volatility skew of S&P 500 index options and VIX. We examine a range of microstructure variables including the level of order flow toxicity in the market using VPIN metric. Results document a statistically significant relation between slope and order flow toxicity even after controlling for liquidity, volatility and momentum effects, transaction costs and net buying pressure. In this respect, option pricing models may benefit from incorporating a measure of market makers' adverse selection risk.

The thesis further analyzes changes in VIX and stock market volatility in response to announcements. Results show a statistically significant relation between VIX and macroeconomic announcements even after controlling for liquidity, volatility and momentum effects. Stock market volatility responds to presidential rhetoric besides macroeconomic announcements. These imply that portfolio managers do pay attention to macroeconomic announcements and presidential rhetoric.

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